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# Mediating Role of Brand Perception and Big Data Analytics between Consumer Experiential Components and Consumer Behavior

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**Abstract**
The study aims to explore the mediating roles of brand perception and big data analytics between consumer experiential components and consumer behavior. It seeks to understand how these factors collectively influence consumer satisfaction and loyalty in a digital marketplace. A structured survey questionnaire was designed and distributed among consumers. Data were collected from 300 respondents, primarily from urban areas. The collected data were analysed using PLS-SEM with SmartPLS4 to test the hypotheses and examine the relationships between the variables. The results revealed that customer experience and cultural influence have significant positive impacts on consumer behavior. However, product characteristics, digital marketing strategy, brand perception, and big data analytics did not show significant direct effects. The study also found that brand perception and big data analytics did not significantly mediate the relationships between the experiential components and consumer behavior. The findings provide valuable insights for businesses aiming to enhance consumer engagement and satisfaction. By focusing on improving customer experience and aligning marketing strategies with cultural influences, businesses can better influence consumer behavior. Additionally, leveraging big data analytics for deeper consumer insights can further refine marketing strategies. This study is one of the first to investigate the combined mediating roles of brand perception and big data analytics in the relationship between consumer experiential components and consumer behavior. The insights from this research contribute to the theoretical understanding and practical application of these concepts in enhancing consumer satisfaction and loyalty.

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***Keywords**: Consumer behavior, Brand perception, Big data analytics, Customer experience, Cultural influence.*

## 1. Introduction

There has been a huge change in the relationship between customer experience and purchasing decisions nowadays, mainly because of the continuously changing market (Yi et al., 2024). Subsequently, business owners need to re-evaluate their strategies, moving their concentration more towards digital arrangements, e-commerce, and innovative marketing techniques (Jiang et al., 2021). As consumer behavior becomes increasingly multifaceted, understanding the intricate relationships between consumers' experiential components, such as cultural and personal influences, and purchase decisions is critical. Additionally, acknowledging how respondents' varying levels of understanding of technical concepts like big data analytics might shape their perceptions adds a layer of complexity that demands careful consideration. In this context, the interplay between big data analytics and brand perception has become increasingly important, as these factors mediate consumer decisions in significant ways (Purwanto & Prayuda, 2024). Big data analytics has become a potent tool that provides businesses with critical insights into consumer preferences and behaviors, enabling the creation of personalized and impactful consumer experiences (Akter & Wamba, 2016). However, its application and effectiveness can vary across industries, highlighting the importance of understanding industry-specific implications in refining marketing strategies. The perceptual nuances connected to brand interactions, combined with the digital revolution, have reshaped the landscape of consumer behavior. These elements work together to form a complex web of influences, making it crucial to understand the mediating factors affecting consumer decisions (Rajasa et al., 2023; Romaniuk & Sharp, 2003).

Despite its promise, the role of big data analytics in enhancing digital marketing strategies requires further exploration, especially to explain why digital marketing strategies may not always translate to significant direct effects on consumer behavior, as observed in this study. This paradox indicates a gap in aligning marketing strategies with consumer expectations and highlights the necessity for contextualized and targeted approaches. The integration of big data analytics and brand perception has become a cornerstone for businesses targeting enhanced consumer experiences and influencing purchasing decisions (Mahmudlu & Muzaffarli, 2024). By analyzing vast datasets, businesses can uncover previously hidden patterns and trends, allowing them to adjust strategies more effectively to meet consumer needs (Chen et al., 2012). This ability to personalize interactions and improve customer satisfaction through data-driven insights has transformed how businesses operate (Bahrami & Shokouhyar, 2022). However, the effectiveness of big data analytics may also depend on the level of awareness and comprehension among consumers, which could vary widely. Furthermore, the mediating role of these factors across different industries and cultural contexts remains underexplored, leaving room for further research into their broader applicability. In a rapidly digitizing world where consumer interactions with brands are increasingly mediated by technology, understanding the interplay between these variables becomes crucial for businesses seeking effective strategies. Aligned with contemporary literature and insights from referenced studies, this research aims to contribute valuable perspectives on the mediating forces shaping consumer behavior in the context of brand perception and big data analytics (Hong & Wyer, Jr., 1989; Kasali et al., 2020). However, the existing literature largely focuses on individual facets of these concepts rather than their combined impact. Additionally, while consumer behavior patterns evolve rapidly, contextual variables such as industry type and regional cultural nuances must be considered to enhance generalizability.

Our study seeks to fill this gap by holistically examining how brand perceptions, driven by customer experiential components and insights derived from big data analytics, collectively influence consumer behavior. By expanding on the underexplored mediating effects of brand perception and big data analytics, we aspire to provide a robust framework for academic discourse and actionable insights for businesses. This study also acknowledges its focus on specific cultural contexts, encouraging future research to validate findings across diverse markets and industries. By leveraging insights from this research, businesses can enhance consumer engagement, improve brand loyalty, and achieve long-term success in an increasingly competitive digital world (Chaffey & Smith, 2022; Meyer & Schwager, 2007).

## 2. Literature Review and Hypotheses Development

The current study reviewed several theoretical models to identify the determinants of consumer behavior, with a specific focus on the mediating roles of brand perception and big data analytics. Among the foundational theories, Davis's Technology Acceptance Model (TAM) is essential for understanding the adoption of cutting-edge technology. This model suggests that a user's intention to use new technology is influenced by perceived ease of use and usefulness (Davis, 1989). To expand on this, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) incorporates additional factors like price value, habit, and hedonic motivation, providing a comprehensive lens to analyze how digital tools like big data analytics influence consumer behavior (Venkatesh et al., 2012). These theories not only guide the exploration of big data analytics but also provide insights into consumer technology adoption behaviors across diverse industries, highlighting the potential variability in its application and effectiveness. The Service Quality Theory (Servqual), developed by Parasuraman, assesses service quality in relation to brand perception through dimensions such as responsiveness, tangibility, assurance, empathy, and reliability (Zeithaml et al., 1988). This framework is particularly relevant for understanding how customer experiences and satisfaction influence consumer behavior and brand perception. Additionally, the Diffusion of Innovations (DOI) theory by Singhal and Rogers (2012) emphasizes the role of communication channels and social systems in technology adoption, offering valuable insights into the relationship between big data analytics and consumer behavior. These theoretical models allow us to contextualize how consumers in specific cultural and industry settings adopt and respond to innovations. To address potential gaps, the study also considers how variations in respondent familiarity with technical concepts, like big data analytics, could influence their responses. Recognizing these variations is essential for ensuring robust theoretical applications and interpreting results with greater accuracy. These theoretical models collectively form the foundation of this study, enabling an exploration of how experiential components, brand perception, and big data analytics interact to influence consumer behavior. This section builds on these theories to develop specific hypotheses and examine their relevance in various cultural, industrial, and digital contexts.

### *2.1 Customer Experience and Satisfaction and Consumer Behavior*

Customer experience (CE) encompasses all interactions a customer has with a brand, from initial awareness to post-purchase engagement (Meyer & Schwager, 2007). Research consistently shows that positive customer experiences lead to greater satisfaction, loyalty, and advocacy (Verhoef et al., 2009). For instance, satisfied customers are more likely to engage in repeat purchases and recommend the brand to others (Gupta & Zeithaml, 2006). In this study, customer experience includes product quality, service interactions, and brand perception, while satisfaction reflects consumers' subjective evaluation of these experiences against expectations (Oliver, 1980). The inclusion of cultural nuances ensures a deeper understanding of how customer experience varies across industries and regions. Given the strong link between customer experience, satisfaction, and behavior, it is hypothesized:

***H1****: Customer Experience (CE) positively influences Consumer Behavior (CB).*

### *2.2 Product Characteristics and Consumer Behavior*

Product characteristics refer to the tangible and intangible attributes that shape consumer perceptions and evaluations, including quality, design, functionality, and brand reputation (Keller, 1993; Man, 2016). Empirical studies indicate that positive perceptions of product characteristics enhance consumer satisfaction and purchase intentions (Dodds et al., 1991; Zeithaml et al., 1988). Notably, unique features and design aesthetics contribute to strong brand perceptions (Kim et al., 2009). The study also explores whether product characteristics' influence on consumer behavior differs across industry settings, given the varying importance of features like design and quality in specific markets. Thus, it is hypothesized:

***H2****: Product Characteristics (PC) positively influence Consumer Behavior (CB).*

### *2.3 Cultural Influence and Consumer Behavior*
Cultural influence encompasses societal norms, values, customs, and beliefs that shape consumer preferences and decision-making (Hofstede, 1980). Cultural symbols and meanings play a pivotal role in shaping brand perceptions and purchase intentions (Littrell & Miller, 2001; Liu & Zhao, 2024). Studies demonstrate that cultural values influence individual preferences for product attributes and consumption patterns (Lee et al., 2011; Hong & Wyer, Jr., 1989). Recognizing the impact of cultural nuances on consumer behavior, the study also seeks to generalize findings to broader contexts by considering cross-cultural variability. Accordingly, it is hypothesized:
***H3**: Cultural Influence (CI) has a positive impact on Consumer Behavior (CB).*

### *2.4 Digital Marketing Strategy and Consumer Behavior*
Digital marketing strategies encompass a wide array of online tools and platforms used to engage customers, promote products, and drive specific behaviors (Chaffey & Smith, 2022). Personalized and targeted advertising has been shown to enhance consumer experiences and drive conversions (Bilal et al., 2020; Salhab et al., 2023). However, this study acknowledges that the effectiveness of digital marketing strategies can vary across industries and demographic contexts. It further examines why certain strategies may fail to generate significant consumer impact, as seen in specific cases, providing insights into the alignment between digital campaigns and consumer expectations. Given its critical role, it is hypothesized:
***H4**: Digital Marketing Strategy (DMS) positively influences Consumer Behavior (CB).*

### *2.5 Brand Perception and Consumer Behavior*
Brand perception refers to the subjective assessments and associations consumers form about a brand (Keller, 1993). Favorable brand perceptions drive loyalty, trust, and preference, as demonstrated by numerous studies (Man, 2016; Wang & Yang, 2011). This study explores how brand perception shapes consumer behavior while considering industry-specific impacts, recognizing that brand perception's importance may differ between industries like technology, luxury, and fast-moving consumer goods. It is hypothesized:
***H5**: Brand Perception (BP) positively influences Consumer Behavior (CB).*

### *2.6 Big Data Analytics and Consumer Behavior*
Big data analytics involves processing vast amounts of data to uncover patterns, trends, and insights that guide strategic decisions (Kasali et al., 2020). Research highlights its role in enabling personalized marketing, recommendation systems, and enhanced customer engagement (Lehrer et al., 2018; Perera et al., 2018). The study acknowledges that the effectiveness of big data analytics may depend on consumer familiarity and comprehension, which could shape how they engage with data-driven experiences. Given its transformative impact, it is hypothesized:
***H6**: Big Data Analytics (BDA) positively influences Consumer Behavior (CB).*

### *2.7 Mediating Effect of Brand Perception and Consumer Behavior*
The mediating effect of brand perception suggests that brand perception acts as an intermediary mechanism through which other factors influence consumer behavior. In this context, brand perception serves as a lens through which consumers interpret and evaluate their interactions with brands, ultimately influencing their behavioural responses. Research suggests that brand perception can mediate the relationship between various factors and consumer behavior. Studies by (Yoo et al., 2000) and (Erdem & Swait, 1998), for instance, have shown how brand perception mediates the relationship between brand features and customer preferences. Research conducted by (Atilgan et al., 2005) and (Keller, 1993) further demonstrated how brand perception functions as a mediator in the relationship between advertisements and customer intentions to purchase. Within the context of this investigation, it is hypothesized that brand perception functions as a mediator in the connections among customer experience, product attributes, cultural impact, digital marketing tactics, and consumer conduct. This implies that consumers' perceptions of a brand shape how their experiences, product features, cultural

factors, and digital marketing efforts influence their behavior. The specific hypotheses related to the mediating effect of brand perception are as follows:
***H7****: Brand Perception (BP) mediates the relationship between Customer Experience (CE) and Consumer Behavior (CB).*
***H8****: Brand Perception (BP) mediates the relationship between Product Characteristics (PC) and Consumer Behavior (CB).*
***H9****: Brand Perception (BP) mediates the relationship between Cultural Influence (CI) and Consumer Behavior (CB).*
***H10****: Brand Perception (BP) mediates the relationship between Digital Marketing Strategy (DMS) and Consumer Behavior (CB).*

### *2.8 Mediating Effect of Big Data Analytics and Consumer Behavior*

The mediating effect of big data analytics suggests that big data analytics serves as an intermediary mechanism through which other factors influence consumer behavior. In this regard, big data analytics gives companies insightful knowledge about the interests and actions of their customers, empowering them to decide wisely and adjust their tactics as necessary. Research suggests that big data analytics can mediate the relationship between different factors and consumer behavior. Research by (Bahrami & Shokouhyar, 2022) and (Chen et al., 2012), for example, has shown how big data analytics act as a mediator between customer behavior and digital marketing techniques. Big data analytics is proposed in this study to operate as a mediator in the interactions between consumer behavior, digital marketing strategy, cultural influence, product attributes, and customer experience. This implies that the insights derived from big data analytics shape how customer experiences, product attributes, cultural factors, and digital marketing efforts influence consumer behavior. The specific hypotheses related to the mediating effect of big data analytics are as follows:
***H11****: Big Data Analytics (BDA) mediates the relationship between Customer Experience (CE) and Consumer Behavior (CB).*
***H12****: Big Data Analytics (BDA) mediates the relationship between Product Characteristics (PC) and Consumer Behavior (CB).*
***H13****: Big Data Analytics (BDA) mediates the relationship between Cultural Influence (CI) and Consumer Behavior (CB).*
***H14****: Big Data Analytics (BDA) mediates the relationship between Digital Marketing Strategy (DMS) and Consumer Behavior (CB).*
These hypotheses aim to address gaps in the literature by exploring the mediating roles of brand perception and big data analytics while accounting for cultural, industrial, and comprehension-based variability. By synthesizing these relationships, the study seeks to provide a robust framework for understanding consumer behavior in the digital age.

### 2.9 Research Framework

This study's theoretical framework integrates prior research to examine the relationships between key consumer experiential components, mediating variables, and consumer behavior (CB). Specifically, it explores how customer experience (CE), product characteristics (PC), cultural influence (CI), and digital marketing strategy (DMS) impact consumer behavior, while considering the mediating roles of brand perception (BP) and big data analytics (BDA). Customer Experience (CE) is a multifaceted construct that encompasses all interactions a consumer has with a brand, from initial awareness to post-purchase engagement (Meyer & Schwager, 2007). Numerous studies have demonstrated that positive customer experiences lead to heightened satisfaction, loyalty, and advocacy, which directly influence consumer behavior (Verhoef et al., 2009). Additionally, consumers evaluate their experiences based on factors such as product quality, service interactions, and brand perception, often comparing them to their expectations (Oliver, 1980). Thus, CE plays a crucial role in driving both consumer satisfaction and behavior, as evidenced by its direct influence on customer loyalty and repeat purchases.

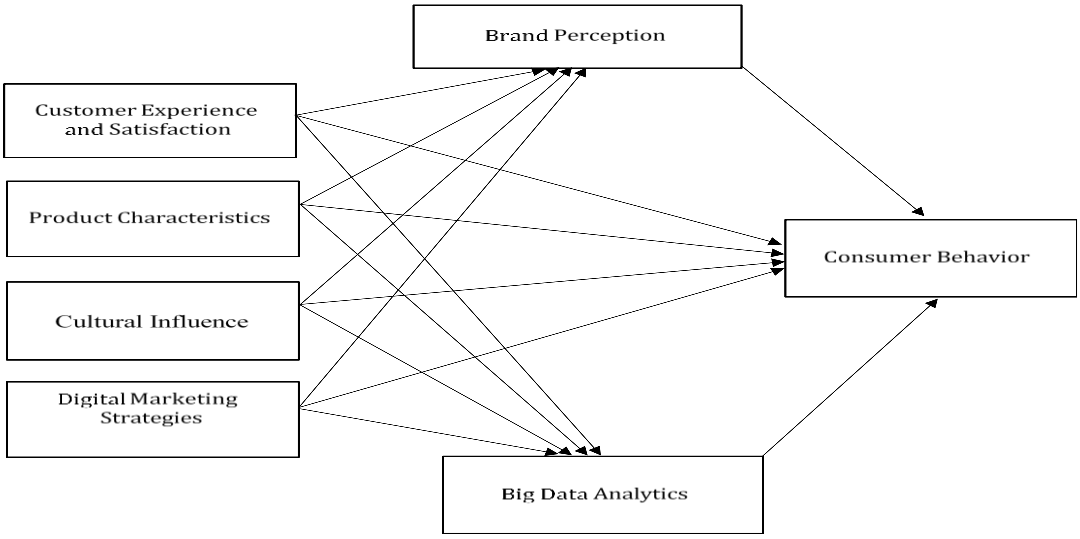


**Figure 1**: Research framework (source: researchers own work)

Product Characteristics (PC), including attributes such as quality, design, functionality, and brand reputation, are central to shaping consumer perceptions and evaluations (Keller, 1993; Man, 2016). Research indicates that positive perceptions of these characteristics enhance consumer satisfaction and purchasing intentions (Dodds et al., 1991; Zeithaml et al., 1988). Additionally, unique product features, such as innovative design and superior quality, can significantly strengthen brand perceptions and consumer loyalty (Kim et al., 2009). Therefore, PC plays an essential role in shaping consumer evaluations and influencing behavioral responses. Cultural Influence (CI), which refers to societal norms, values, and beliefs, plays a pivotal role in shaping consumer preferences and decision-making (Hofstede, 1980). Cultural values and symbols influence how consumers perceive brands and make purchasing decisions (Littrell & Miller, 2001; Liu & Zhao, 2024). Furthermore, studies have shown that cultural differences significantly affect consumption patterns and preferences for product attributes (Lee et al., 2011; Hong & Wyer, Jr., 1989). Thus, CI is crucial for understanding how cultural factors shape consumer interactions with brands and influence their purchasing behavior. Digital Marketing Strategy (DMS) involves the use of various online tools and platforms to engage consumers, promote products, and influence consumer behavior (Chaffey & Smith, 2022). Personalization and targeted advertising are key components of effective DMS, enhancing consumer experiences and driving conversions (Bilal et al., 2020). However, the effectiveness of DMS can vary across industries and consumer demographics, with the alignment between digital campaigns and consumer expectations playing a critical role in their success (Salhab et al., 2023). Therefore, understanding the role of DMS is essential in explaining how digital interactions influence consumer behavior. Brand Perception (BP) reflects the subjective impressions and associations that consumers form about a brand (Keller, 1993). Positive brand perceptions are linked to consumer loyalty, trust, and preference (Erdem & Swait, 1998; Wang & Yang, 2011). BP also acts as a mediator in the relationship between various experiential components and consumer behavior, as it serves as a lens through which consumers interpret their interactions with brands (Yoo et al., 2000; Atilgan et al., 2005). In this sense, BP plays an intermediary role in the connections between customer experience, product characteristics, cultural influence, digital marketing strategy, and consumer behavior. Big Data Analytics (BDA) involves processing large volumes of data to identify patterns, trends, and insights that guide strategic decisions (Lehrer et al., 2018; Perera et al., 2018). BDA enables businesses to personalize marketing efforts and enhance customer engagement, thereby improving the customer experience and influencing consumer behavior. Additionally, BDA plays a transformative role in linking experiential components with consumer behavior, offering companies deeper insights into customer preferences and behaviors (Chen et al., 2012; Bahrami

& Shokouhyar, 2022). Moreover, BDA shapes how consumers perceive brands and engage with digital marketing efforts, thereby influencing overall consumer behavior.

Moreover, this framework integrates these experiential components and mediators to provide a comprehensive understanding of how customer experience, product characteristics, cultural influence, digital marketing strategies, brand perception, and big data analytics collectively shape consumer behavior. This approach offers valuable insights into the mechanisms driving consumer engagement, satisfaction, and loyalty in the digital marketplace. Although extensive research has explored the determinants of consumer behavior, there is a distinct opportunity to examine the mediating roles of brand perception and big data analytics within this relationship. Investigating these mediating roles will enhance our understanding of consumer habits in the digital age and provide practical insights for businesses seeking to optimize their strategies. The findings will address existing research gaps and offer a deeper understanding of the factors influencing consumer behavior, specifically in the context of brand perception and big data analytics. Consequently, the above framework has been developed to guide this study (see Figure 1).

## 3. Methodology

### *3.1 Data Sampling*

Consumers who engage with e-commerce platforms and those with a technical background were chosen as the population for this study, given its focus on understanding consumer behavior influenced by brand perception and big data analytics. Considering the indeterminate size of the e-commerce user population, regular users and technically expert users of e-commerce services were selected as the sampling frame. The methodology of non-probability purposive sampling (Shinija et al, 2023) was employed to ensure the inclusion of respondents relevant to the study objectives. To collect data efficiently, structured questionnaires were distributed via Google Forms, targeting 350 respondents. This digital approach enabled broad-reaching data collection and provided convenience for participants. Of the 350 distributed questionnaires, 318 were returned, with 300 deemed usable after addressing missing data and ensuring data normality (Sarstedt et al., 2017). The sample size aligns with recommendations for structural equation modeling (SEM), as approximately 300 respondents are considered sufficient for robust and reliable analysis (Shneif, 2015). To enhance credibility, the study acknowledges potential biases inherent in non-probability sampling, such as over-representation of tech-savvy individuals. This bias may limit the generalizability of findings, particularly to populations with differing levels of technical exposure or digital literacy (Reddy et al., 2023). To mitigate these effects, the study emphasizes future adoption of probability sampling methods to validate these results across more diverse demographics. Additionally, variations in respondents' familiarity with complex constructs like big data analytics are considered as a potential limitation, which could have influenced the findings. Future research could address this by employing training sessions, explanatory notes, or workshops during data collection to ensure respondents comprehend the key concepts being measured.

### *3.2 Measurement Instrument*

The measurement instrument employed in this study was a structured questionnaire designed using a five-point Likert scale (Joshi et al., 2015). The questionnaire was grounded in established research, ensuring both validity and reliability. Key constructs measured included customer experience and satisfaction, product characteristics, cultural influence, brand perception, and big data analytics. Items measuring customer experience and satisfaction focused on aspects such as service quality, emotional response, and overall customer interactions. Questions on product characteristics addressed perceptions of quality, uniqueness, and suitability, while cultural influence items reflected societal values, norms, and their impact on decision-making. Brand perception was evaluated through metrics like brand trust, image, and reputation. Lastly, big data analytics was assessed by exploring the effectiveness of data utilization in enhancing customer interactions. This comprehensive approach ensured a nuanced understanding of how brand perception and big data analytics mediate the relationship between consumer experiences and behavior. Pre-testing of the questionnaire with a small group of respondents was conducted to ensure clarity, relevance, and alignment with the study objectives. The study also highlights potential limitations in respondent understanding of technical concepts like big data analytics, which could lead to skewed results (Hammouri et al., 2020). To address this, future research could include detailed explanations of technical terms or the provision of real-world examples to facilitate better comprehension among participants.

### *3.3 Data Analysis Techniques*

To ensure reliability and credibility, two statistical tools were used for data analysis: SmartPLS4 and SPSS20. SmartPLS4 facilitated the examination of measurement and structural models, while SPSS20 was used for descriptive statistics and to validate the suitability of the data for further analysis. The study employed partial least squares structural equation modeling (PLS-SEM) to analyze the relationships between variables. This approach was chosen for its effectiveness in evaluating complex models and its robustness in handling multivariate data (Reisinger & Mavondo, 2007). PLS-SEM is particularly well-suited for exploratory research, as it supports the simultaneous examination of multiple dependent and independent variables. The analysis followed a two-step approach. First, a measurement model was proposed to assess the validity and reliability of the constructs, ensuring that the items accurately measured their intended latent variables. This included calculating metrics such as Cronbach's alpha, composite reliability, and average variance extracted (AVE). Second, a structural model was developed to test the proposed hypotheses and evaluate the significance of relationships between constructs. The results provided evidence to support or reject the hypotheses, offering valuable insights into the mediating roles of brand perception and big data analytics. To enhance the rigor of the analysis, this study emphasizes the need for transparency in reporting biases and limitations within the data. For example, it recognizes that respondent biases, particularly related to varying levels of digital literacy and cultural differences, might have influenced their engagement with the survey. These factors are noted as areas for refinement in future research. The methodological rigor employed in this study, including robust sampling and statistical analysis, ensures the credibility of the findings. However, the study also acknowledges that the industry-specific nature of the results may limit their generalizability. Future research could broaden the scope by testing the relationships across different industries to better understand how varying market dynamics influence consumer behavior.

## 4. Data Analysis

### *4.1Respondents' profile*

Table 4.1 presents the demographic characteristics of the respondents of the study. The respondents include a mix of age groups, with the majority being between 35-44 years old (46.33%), followed by 25-34 years old (43.00%). Regarding gender, 59.00% of the respondents are male and 41.00% are female. In terms of educational qualifications, 53.34% of the respondents have completed post-graduation, 43.33% have completed graduation, and 3.33% have post-graduation with other degrees such as MPhil/PhD. Therefore, among the respondents, 56.67% have at least a post-graduate degree, indicating a high level of education among the study participants. Regarding professional experience, the majority of respondents have 1-3 years of experience (58.33%), followed by those with 4-6 years of experience (36.00%). A small proportion of respondents have 7-9 years (3.00%) and 10 or more years (2.67%) of professional experience. The demographic characteristics of the respondents and their distribution across different age groups, gender, education levels, and professional experience demonstrate the sufficiency and diversity of the sample for the current study.

**Table 4.1**: Demographic characteristics of the respondents

| | | Frequency | Percent |
|---|---|---|---|
| **Age** | 25-34 Years | 129 | 43 |
| | 35-44 Years | 139 | 46.33 |
| | 45-54 Years | 30 | 10 |
| | 55 and above | 2 | 0.67 |
| **Gender** | Female | 123 | 41 |
| | Male | 177 | 59 |
| **Educational Qualification** | Graduation | 130 | 43.33 |
| | Post-Graduation | 160 | 53.34 |
| | Post-Graduation with other degrees (MPhil/PhD etc.) | 10 | 3.33 |
| **Professional Experience** | 1-3 Years | 175 | 58.33 |
| | 4-6 Years | 108 | 36 |
| | 7-9 Years | 9 | 3 |
| | 10 or above Years | 8 | 2.67 |

***Source:*** *researchers own work based on SPSS output*

### *4.2 Measurement Model*

#### *4.2.1 Factor loading, reliability and convergent validity analysis*

**Table 4.2**: Item loading, convergent validity and reliability

| Variables | Items | Loading Value | Cronbach's Alpha (CA) | Composite Reliability (CR) (rho_c) | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|
| Customer Experience and Satisfaction | CE3 | 0.761 | 0.809 | 0.868 | 0.568 |
| | CE4 | 0.793 | | | |
| | CE5 | 0.793 | | | |
| | CE6 | 0.792 | | | |
| Product Characteristics | PC1 | 0.718 | 0.852 | 0.89 | 0.575 |
| | PC2 | 0.715 | | | |
| | PC3 | 0.738 | | | |
| | PC4 | 0.719 | | | |
| | PC5 | 0.712 | | | |
| | PC6 | 0.781 | | | |
| Cultural Influence | CI1 | 0.753 | 0.905 | 0.928 | 0.683 |
| | CI2 | 0.776 | | | |
| | CI3 | 0.772 | | | |
| | CI4 | 0.734 | | | |
| | CI5 | 0.755 | | | |
| | CI6 | 0.761 | | | |
| Digital Marketing Strategies | DM1 | 0.787 | 0.792 | 0.865 | 0.616 |
| | DM2 | 0.738 | | | |
| | DM3 | 0.713 | | | |
| | DM4 | 0.727 | | | |
| | DM5 | 0.745 | | | |
| | DM6 | 0.762 | | | |
| Brand Perception | BP1 | 0.752 | 0.852 | 0.891 | 0.576 |
| | BP2 | 0.754 | | | |
| | BP3 | 0.798 | | | |
| | BP4 | 0.721 | | | |
| | BP5 | 0.805 | | | |
| | BP6 | 0.717 | | | |
| Big Data Analytics | BD1 | 0.706 | 0.841 | 0.882 | 0.556 |
| | BD2 | 0.793 | | | |
| | BD3 | 0.735 | | | |
| | BD4 | 0.793 | | | |
| | BD5 | 0.737 | | | |
| Consumer Behavior | CB2 | 0.752 | 0.826 | 0.873 | 0.534 |
| | CB3 | 0.754 | | | |
| | CB4 | 0.798 | | | |
| | CB6 | 0.721 | | | |
| | CB7 | 0.806 | | | |
| | CB8 | 0.717 | | | |

***Source:*** *researchers own work based on SmartPLS output*

The degree to which each item in the correlation matrix correlates with the specified principal component is indicated by factor loading. The individual item dependability is evaluated by examining the standardized loadings, also known as simple correlation. 44 items are used in the study to measure the latent components in order to determine the factors that influence consumer behavior. The factor loading is shown in Table 4.2, and the loading score is enough for measuring the constructs. Because of their low loading scores or in order to get adequate scores for Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) for additional analysis, the items CE1, CE2, BD6, CB1, and CB5 were eliminated from the model. The CA method and CR are also used in this study's reliability measurement. Values over 0.7 in the commonly used CA reliability metric denote satisfactory dependability (Nunnally, 1978). Although CA is a widely used criterion to evaluate the reliability of variables, hybrid reliability, a more modern criterion, is applied in the PLS technique. The CR result has been used in this criterion. When the value is more than 0.7, this suggests that the model has strong internal consistency (Hair et al., 2019). It is recommended that CR be used instead of CA, which gives all indications the same weight, because it considers the varying weights of the indicators. 0.7 (Jr. et al., 2017). In order to determine how much variation latent variables, assess from their items that are meant to test them proportionate to the disparity that happened for measurement errors, the following criteria, called AVE, is essential. An average allowable variance is shown by an AVE value greater than 0.5 (Hair et al., 2019; Henseler et al., 2015) Following the threshold of 0.70, the CA value of the constructs has been assessed and consequently, the constructs have shown good reliability, as the CA of the constructs ranges from 0.792 to 0.905. Furthermore, all variables had CRs greater than 0.70. This indicates that the items are suitable for measuring the structures. For all factors combined, the AVE is greater than 0.5. The suggested model is deemed suitable at the standard level in accordance with the introduced criteria.

### *4.2.2 Discriminant validity*

Prior to measuring discriminant validity, convergent validity was examined in order to determine how unique the construct is from the others. Discriminant validity guarantees the uniqueness of every construct (Hair et al., 2012). For conceiving discriminant validity, the Fornell and Larker criterion is an efficacious method. Each latent variable should show a higher degree of square root of AVE (the diagonal values) based on this study than the constructs' correlation values with other variables (Fornell & Larcker, 1981). Table 4.3 demonstrates that in the specified columns and rows, diagonal values are bigger than off diagonal values. As a result, the model's discriminant validity analysis finds that there is no significant problem with multi collinearity and that the latent variables are discrete.

**Table 4.3:** Correlations among the constructs (Fornell and Larker test)

| | BD | BP | CB | CE | CI | DM | PC |
|---|---|---|---|---|---|---|---|
| BD | **0.754** | | | | | | |
| BP | 0.679 | **0.759** | | | | | |
| CB | 0.305 | 0.32 | **0.827** | | | | |
| CE | 0.562 | 0.629 | 0.211 | **0.785** | | | |
| CI | 0.621 | 0.663 | 0.351 | 0.646 | **0.759** | | |
| DM | 0.637 | 0.597 | 0.28 | 0.573 | 0.599 | **0.746** | |
| PC | 0.657 | 0.631 | 0.301 | 0.594 | 0.68 | 0.63 | **0.731** |

***Source:*** *researchers own work based on SmartPLS output*

Another method, the HTMT ratio, provides a direct assessment of discriminant validity by comparing the magnitudes of inter-construct correlations with the AVE. This ratio is less susceptible to bias due to the absence of distributional assumptions, and it provides more accurate results, particularly in situations involving non-normal data on a small sample size (Hair et al., 2011). Shneif (2015) suggested a strict approach for HTMT with a cut-off value of 0.85, while (Hair et al., 2019) affirmed a 0.90 threshold value to analyse discriminant validity. The results in Table 4.4 show satisfactory discriminant validity as the values obtained the stringent threshold value, where HTMT <0.85. So, both convergent reliability and discriminant validity of the study demonstrated satisfactory reliability and validity of the constructs, and these are available for the analysis of the structural model.

**Table 4.4**: Heterotrait-monotrait (HTMT) ratio

| | BD | BP | CB | CE | CI | DM | PC |
|---|---|---|---|---|---|---|---|
| BD | | | | | | | |
| BP | 0.815 | | | | | | |
| CB | 0.357 | 0.36 | | | | | |
| CE | 0.698 | 0.762 | 0.25 | | | | |
| CI | 0.744 | 0.772 | 0.4 | 0.786 | | | |
| DM | 0.764 | 0.696 | 0.321 | 0.692 | 0.701 | | |
| PC | 0.798 | 0.746 | 0.345 | 0.733 | 0.807 | 0.75 | |

***Source:*** *researchers own work based on SmartPLS output*

### *4.2.3 Explanatory power of the model*

Moreover, R2, the coefficient of determination indicates the predictive power of the model of the variables. While the value of R2 (0.7, 0.5, and 0.2) denotes the substantial, moderate, and weak predictive power of the variables respectively (Hair et al., 2019; Henseler et al., 2015). Here in Table 4.5 the value of R2 stood at 0.150 which indicates the independent variable has weak predictive power to explain the dependent variable (CB) and R2 of 0.557 & 0.545 which means that approximately 55.7% & 54.5% of the variance in the mediator (BP) & BD can be explained by the independent variable and has moderate predictive power.

**Table 4.5**: Results of R2

| | R-square |
|---|---|
| BD | 0.545 |
| BP | 0.557 |
| CB | 0.150 |

***Source:*** *researchers own work based on SmartPLS output*

### *4.3 Structural model*

The structural model in research enables us to understand the relation between the independent variables and dependent variables (Ramlall, I. 2016). In the table, all the variables and the respective β value, Standard Deviation, t-value, and p-values have been shown. The P value is utilized to measure the significant of hypothesized relationships between independent variables and dependent variables. The β indicates the extent to which the dependent variable fluctuates when the independent variable changes. While P value shows the variance between the independent and dependent variables depicting the significance level at 0.05 ($P < .05$).

### *4.3.1 Results of direct path analysis*

Table 4.6 presents the results of all the direct paths with their coefficient values (β) along with the t-statistics and p-values of the individual paths. The weight of the p-value determines whether the hypotheses proposed by the author will be accepted or not. Here CE (H1: CE ->CB β= 0.389, Standard Deviation SD= 0.127, t=3.071 and P=0.002) is positively related to CB since the significance level is smaller than the required 0.05.

On the other hand, PC (H2: PC -> CB, β=0.055, SD = 0.071, t=0.77 and P=0.441) has no positive impact on CB. Conversely CI (H3: CI -> CB, β=0.23, SD = 0.094, t=2.445 and P=0.015) has positive impact on CB and the results are statistically significant at level. Again, DM (H4: DM -> CB, β=0.056, SD=0.084, t=0.66 and P=0.509) has no positive impact on CB. Similarly, BP (H5: BP -> CB, β=0.128, SD=0.07, t=1.834 and P=0.067) has no positive impact on CB. Also, BD (H5: BD -> CB, β=0.073, SD=0.107, t=0.681 and P=0.496) has no positive impact on CB.

**Table 4.6:** Results of direct path analysis

| Hypothesis | Path | β | SD | T statistics | P values | Results |
|---|---|---|---|---|---|---|
| H1 | CE -> CB | 0.389 | 0.127 | 3.071 | 0.002 | Supported |
| H2 | PC -> CB | 0.055 | 0.071 | 0.77 | 0.441 | Not Supported |
| H3 | CI -> CB | 0.23 | 0.094 | 2.445 | 0.015 | Supported |
| H4 | DM -> CB | 0.056 | 0.084 | 0.66 | 0.509 | Not Supported |
| H5 | BP -> CB | 0.128 | 0.07 | 1.834 | 0.067 | Not Supported |
| H6 | BD -> CB | 0.073 | 0.107 | 0.681 | 0.496 | Not Supported |

***Source:*** *researchers own work based on SmartPLS output*

### *4.3.2 Results of indirect path analysis*

In addition to the direct path analysis, the study examines whether BP & BD acts as a catalyst between predictors and predicted variables. The results of H7 (CE -> BP -> CB, β=0.03, SD = 0.022, t = 1.396 and p = 0.163), H8 (PC -> BP -> CB, β=0.025, SD = 0.017, t = 1.463 and p = 0.144), H9 (CI -> BP -> CB, β=0.035, SD = 0.021, t = 1.626 and p = 0.104), H10 (DM -> BP -> CB, β=0.023, SD = 0.015, t = 1.543 and p = 0.123), H11 (CE -> BD -> CB, β=0.008, SD = 0.014, t = 0.553 and p = 0.58), H12 (PC -> BD -> CB, β=0.021, SD = 0.031, t = 0.682 and p = 0.495), H13 (CI -> BD -> CB, β=0.014, SD = 0.023, t = 0.591 and p = 0.554) and finally H14 (DM -> BD -> CB, β=0.021, SD = 0.033, t = 0.614 and p = 0.539), all of them fail to establish a significant mediating effect of BP & BD among CE,PC,CI and PC respectively. (Table 4.7)

**Table 4.7**: Results of specific indirect effect

| Hypothesis | Path | β | SD | T statistics | P values | Results |
|---|---|---|---|---|---|---|
| H7 | CE -> BP -> CB | 0.03 | 0.022 | 1.396 | 0.163 | Not Supported |
| H8 | PC -> BP -> CB | 0.025 | 0.017 | 1.463 | 0.144 | Not Supported |
| H9 | CI -> BP -> CB | 0.035 | 0.021 | 1.626 | 0.104 | Not Supported |
| H10 | DM -> BP -> CB | 0.023 | 0.015 | 1.543 | 0.123 | Not Supported |
| H11 | CE -> BD -> CB | 0.008 | 0.014 | 0.553 | 0.58 | Not Supported |
| H12 | PC -> BD -> CB | 0.021 | 0.031 | 0.682 | 0.495 | Not Supported |
| H13 | CI -> BD -> CB | 0.014 | 0.023 | 0.591 | 0.554 | Not Supported |
| H14 | DM -> BD -> CB | 0.021 | 0.033 | 0.614 | 0.539 | Not Supported |

***Source:*** *researchers own work based on SmartPLS output*

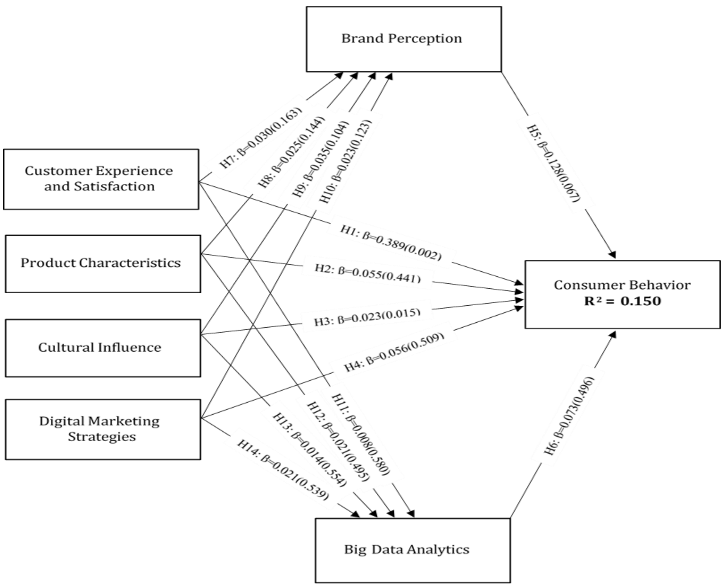


**Figure 2:** shows the result of both direct & indirect paths along with their respective P values (Source SmartPLS Output)

Moreover, the results of the total path analysis are presented in Table 4.8. The BP & BD has a partial mediation effect between CE & CB as the path coefficient has increased in total effect to β

= 0.430 and remained significant at level 0.05. Similarly, the BP & BD has a partial mediation effect between CI & CB as the path coefficient has increased in total effect to β = 0.279 and remained significant at level 0.05.

**Table 4.8:** Results of total path analysis

| Path | β | SD | T statistics | P values | Results |
|---|---|---|---|---|---|
| CE -> CB | 0.430 | 0.984 | 3.325 | 0.001 | Supported |
| PC -> CB | 0.1 | 0.075 | 1.335 | 0.182 | Not Supported |
| CI -> CB | 0.279 | 0.087 | 3.211 | 0.001 | Supported |
| DM -> CB | 0.099 | 0.071 | 1.389 | 0.165 | Not Supported |

***Source:*** *researchers own work based on SmartPLS output*

## 5. Findings and Discussion

This study sought to evaluate the extent to which customer experience, product characteristics, cultural influence, digital marketing strategy, brand perception, and big data analytics influence consumer behavior. Additionally, it investigated the indirect effects of these predictors through the mediating roles of brand perception and big data analytics. The findings indicate that Customer Experience (CE) and Cultural Influence (CI) have a significant positive influence on Consumer Behavior (CB) (Wijaya et al., 2019). Conversely, Product Characteristics (PC), Digital Marketing Strategy (DMS), Brand Perception (BP), and Big Data Analytics (BDA) did not show significant direct effects on Consumer Behavior. These findings highlight the complexity of consumer behavior (Arenas-Gaitán et al., 2019), suggesting that some factors require complementary influences to exert measurable impacts.

Customer Experience emerged as a critical determinant of consumer behavior. It is a strategic process designed to convey important messages effectively to consumers, capturing their attention and meeting their specific needs throughout the entire interaction journey. Customers who experience exceptional and personalized engagement with a brand are more likely to feel connected and loyal. The study emphasizes that businesses focusing on enhancing customer experience—including product quality, customer service, and positive brand perceptions—can significantly influence consumer behavior. This reinforces the importance of a holistic approach, where seamless and engaging experiences drive repeated purchases and long-term loyalty. Cultural Influence plays a pivotal role in shaping consumer behavior. The findings show that societal norms, values, and expectations significantly affect how consumers perceive and interact with brands. Businesses aligning their marketing strategies with cultural nuances are more effective in engaging their target audiences. These results highlight the necessity of integrating cultural insights into business practices to enhance consumer engagement and loyalty. Furthermore, the findings suggest that the impact of cultural alignment may vary across industries, requiring businesses to tailor strategies that account for regional differences. The positive impact of cultural alignment underscores its importance as a strategic lever for businesses aiming to navigate diverse markets successfully. Product Characteristics, while relevant, did not show a significant direct effect on consumer behavior in this study. This suggests that product attributes such as quality, design, and functionality, though important, may not independently determine consumer behavior. Instead, these characteristics might need to be reinforced by other factors like customer experience and cultural alignment to drive consumer decisions effectively. Additionally, industry-specific differences might influence the role of product characteristics, as certain features could hold varying levels of importance depending on the sector. This finding indicates that businesses should view product attributes as one component of a broader, integrated strategy to influence consumer behavior. Digital Marketing Strategy also did not exhibit a significant direct effect on consumer behavior. This finding implies that simply implementing digital marketing tactics is insufficient. The effectiveness of these strategies depends on how well they resonate with consumer expectations and preferences. Personalized, targeted, and contextually relevant marketing efforts are crucial for driving consumer engagement and influencing behavior. Moreover, the results suggest that execution challenges, such as a lack of alignment with industry-specific needs or consumer digital literacy, may dilute the effectiveness of digital marketing campaigns. This highlights the need for businesses to ensure that digital campaigns are thoughtfully executed and tailored to specific audiences. Neither Brand Perception nor Big Data Analytics significantly mediated the relationships between the predictors and consumer behavior. While these factors are valuable for providing supportive insights, their impact on consumer behavior may not be direct or strong enough to serve as primary mediators. Instead, they appear to support other more influential factors such as customer experience and cultural influence. Notably, the effectiveness of these mediators could also vary across industries, with some sectors benefiting more significantly from brand perception or big data-driven strategies. These findings suggest that while brand perception and big data analytics are important tools, their strategic value lies in complementing and enhancing other determinants rather than acting as standalone influencers.

The indirect path analysis revealed that neither Brand Perception (BP) nor Big Data Analytics (BDA) significantly mediated the relationships between Customer Experience, Product Characteristics, Cultural Influence, Digital Marketing Strategy, and Consumer Behavior. Hypotheses related to mediating effects (H7 to H14) were not supported. This highlights that direct influences from customer experience and cultural influence are more critical in determining consumer behavior, while the mediating roles of brand perception and big data analytics remain secondary. The findings underscore the importance of prioritizing customer experience and cultural alignment to influence consumer behavior effectively (Shavitt & Barnes, 2019). Businesses should invest in strategies that enhance the overall customer journey and ensure that their approaches are culturally relevant. These elements are essential for building strong consumer connections and fostering loyalty. Moreover, cross-industry variability in the weightage of these factors suggests that strategies should be customized to specific sectors, ensuring a tailored approach to consumer engagement.

While not primary influencers, brand perception and big data analytics remain valuable tools. Their impact can be amplified when aligned with broader strategic goals, providing supportive insights and enabling businesses to refine marketing efforts. Future studies could explore whether the lack of mediation observed here stems from varying levels of consumer familiarity with these concepts or industry-specific contexts. By leveraging these tools effectively, businesses can enhance engagement, satisfaction, and loyalty in an increasingly competitive market. Product characteristics and digital marketing strategies, though not significant on their own, can have amplified impacts when integrated with customer experience and cultural insights. This highlights the importance of adopting a comprehensive and cohesive approach rather than relying on isolated factors. Moreover, the study emphasizes that these elements might play a more pronounced role in industries where product innovation or digital presence is central to consumer decision-making, suggesting potential areas for deeper exploration.

## 6. Implications and Conclusion

This study focused on the mediating roles of brand perception and big data analytics in shaping consumer behavior through experiential components. The findings indicated that H1 and H3 were significant, with p-values below 0.05, signifying a strong and positive influence on consumer behavior. Specifically, H1, which examined the impact of customer experience on consumer behavior mediated by brand perception, demonstrated a p-value of 0.002, highlighting a significant positive effect. Similarly, H3, which assessed the influence of cultural factors on consumer behavior, had a p-value of 0.015, confirming its significant impact. These results underscore the critical roles of customer experience and cultural alignment in enhancing brand perception, which in turn positively influences consumer behavior. Effective brand management plays a pivotal role in leveraging brand perception to foster personalized consumer interactions and improved loyalty. Businesses can achieve a competitive edge by aligning their marketing strategies with the cultural contexts of their target markets. The significant influence of cultural factors highlights the importance of tailoring strategies to regional and societal nuances, enhancing the overall effectiveness of brand perception strategies. Furthermore, the study underscores that the impact of cultural alignment may vary across industries, requiring a deeper understanding of specific sectoral dynamics to refine strategies. On the other hand, H2, H4, H5, and H6, which examined product characteristics, digital marketing strategies, and big data analytics, did not show significance in their direct paths. While these elements are important, their impact on consumer behavior may require integration with other business functions to achieve meaningful influence. For example, product characteristics and digital marketing strategies may yield stronger results when paired with a robust focus on customer experience and cultural alignment. Additionally, industry-specific nuances should guide the development of digital marketing campaigns and product innovations to ensure relevance and effectiveness.

The findings suggest that brand perception and big data analytics, though not primary influencers, can provide valuable supportive insights when integrated strategically. By leveraging these tools effectively, businesses can refine their understanding of consumer preferences, enabling them to design targeted and impactful marketing strategies. The study also highlights that varying levels of consumer familiarity with big data-driven insights could explain its limited mediation effect. This suggests the need for businesses to educate consumers on the value of data-driven personalization, potentially increasing its impact on decision-making. The study's findings suggest that the importance of specific experiential components, such as product characteristics or digital marketing strategies, may vary significantly across industries. For example, industries like technology or luxury goods might prioritize product innovation and exclusivity, while fast-moving consumer goods may focus more on affordability and mass appeal. Recognizing these industry-specific dynamics is crucial for businesses aiming to tailor their strategies effectively.

**Practical Recommendations:**

a. **Customer-Centric Strategies:** Businesses should prioritize investments in customer experience initiatives, ensuring seamless interactions, quality service, and personalized engagement throughout the consumer journey.
b. **Cultural Customization:** Aligning marketing and operational strategies with regional and societal norms can help businesses build deeper consumer connections, particularly in culturally diverse markets.
c. **Integrated Approaches:** Combining digital marketing strategies and product innovation with strong customer experience frameworks can amplify their impact, rather than relying on isolated efforts.
d. **Big Data Utilization:** Companies should not only adopt advanced data analytics tools but also focus on educating consumers about their benefits, improving their receptiveness to data-driven personalization.
e. **Industry Tailoring:** Businesses should analyze how the relative importance of experiential components varies across their specific industries and adapt strategies accordingly.

This research provides critical insights into the interplay between brand perception, big data analytics, and consumer experiential components, offering a comprehensive framework for businesses aiming to enhance consumer engagement and loyalty. By emphasizing the significance of customer experience and cultural alignment, the study highlights actionable strategies that can drive sustainable consumer connections. While brand perception and big data analytics are not primary influencers, their strategic integration with other determinants can amplify their impact. These tools hold the potential to refine business strategies when aligned with consumer expectations and contextual nuances. The findings also point to the need for further exploration of industry-specific dynamics and the role of consumer familiarity with digital and data-driven concepts. Businesses must remain agile, adapting their approaches to evolving market demands and leveraging emerging technologies like AI and machine learning to better understand and predict consumer behavior. In conclusion, this research underscores the importance of adopting a comprehensive and context-sensitive approach to understanding consumer behavior, ensuring that businesses remain competitive in the rapidly evolving digital marketplace.

## 7. Limitations and Future Research Directions

While this study offers valuable insights into the mediating roles of brand perception and big data analytics, several limitations warrant attention. Firstly, the study primarily focused on specific experiential components, potentially overlooking other factors such as economic conditions, industry-specific dynamics, or emerging market trends, which could also influence consumer behavior. Future research could expand the scope to include these additional variables, providing a more holistic understanding of consumer decision-making. The reliance on data from a single cultural context poses a limitation regarding the generalizability of findings to other regions or markets with differing cultural dynamics. Cross-cultural studies are recommended to validate these findings and explore how cultural differences impact the relationships studied. Additionally, industry-specific variations in the importance of experiential components such as product characteristics and digital marketing strategies highlight the need for research across diverse sectors to better understand how market dynamics influence consumer behavior. Another significant limitation stems from respondents' varying levels of understanding of big data analytics. As a complex concept, big data analytics may have been challenging for some respondents to fully grasp, potentially affecting their ability to provide accurate responses. Future studies could address this by offering explanatory materials, workshops, or real-world examples during data collection to ensure respondents have a clear understanding of technical concepts. This would help mitigate the influence of varying levels of familiarity on the study's outcomes. The study's approach was predominantly quantitative, relying on structured questionnaires. While this provided measurable insights, it may not fully capture the nuanced impressions and attitudes of consumers. Qualitative methods, such as focus groups or in-depth interviews, could complement quantitative approaches, offering richer insights into the motivations behind consumer behavior and the subjective experiences influencing their decisions. Practical and logistical constraints limited the sample size and diversity, which may not adequately represent the broader customer base, particularly in diverse global markets. Expanding the sample size and incorporating a more diverse respondent pool could enhance the generalizability of future findings. Additionally, employing probability sampling techniques could address biases inherent in non-probability methods, ensuring a more representative data set for robust analysis. Longitudinal studies could also provide valuable insights into how consumer behavior evolves over time, particularly as influenced by brand perception and big data analytics. Emerging technologies, such as machine learning and artificial intelligence, present promising avenues for future research. Investigating how these technologies affect consumer behavior and brand perception could yield significant insights, especially in rapidly changing markets. Additionally, understanding the interplay between consumer digital literacy and the effectiveness of data-driven personalization strategies could refine the role of big data analytics as a mediating factor. Finally, exploring the relationships studied in this research across different industries could reveal whether the observed patterns are consistent or vary significantly. Such industry-specific insights could help businesses tailor strategies to enhance consumer engagement and loyalty more effectively. For example, sectors like luxury goods or technology may exhibit distinct consumer behavior patterns compared to fast-moving consumer goods or services. While this study makes significant contributions to understanding the mediating roles of brand perception and big data analytics, the outlined limitations and suggested future research directions highlight the need for continued exploration in this dynamic field. Addressing these limitations will not only improve the validity and applicability of findings but also provide businesses with deeper insights and more effective strategies to navigate the complexities of consumer behavior.

## References


Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: A systematic review and agenda for future research. Electronic Markets, 26(2), 173–194. https://doi.org/10.1007/s12525-016-0219-0

Arenas-Gaitán, J., Sanz-Altamira, B., & Ramírez-Correa, P. E. (2019). Complexity of Understanding Consumer Behavior from the Marketing Perspective. Complexity, 2019(1). https://doi.org/10.1155/2019/2837938

Arici, H. E., Cakmakoglu Arıcı, N., & Altinay, L. (2023). The use of big data analytics to discover customers' perceptions of and satisfaction with green hotel service quality. Current Issues in Tourism, 26(2), 270–288. https://doi.org/10.1080/13683500.2022.2029832

Atilgan, E., Aksoy, Ş., & Akinci, S. (2005). Determinants of the brand equity: A verification approach in the beverage industry in Turkey. Marketing Intelligence & Planning, 23(3), 237–248. https://doi.org/10.1108/02634500510597283

Bahrami, M., & Shokouhyar, S. (2022). The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: A dynamic capability view. Information Technology & People, 35(5), 1621–1651. https://doi.org/10.1108/ITP-01-2021-0048

Bilal, M., Jianqu, Z., & Ming, J. (2020). How Consumer Brand Engagement Effect on Purchase Intention? The Role of Social Media Elements. Journal of Business Strategy Finance and Management, 2(1–2), 44–55. https://doi.org/10.12944/JBSFM.02.01-02.06

Brunk, K. H., & De Boer, C. (2020). How do Consumers Reconcile Positive and Negative CSR-Related Information to Form an Ethical Brand Perception? A Mixed Method Inquiry. Journal of Business Ethics, 161(2), 443–458. https://doi.org/10.1007/s10551-018-3973-4

Chaffey, D., & Smith, P. (2022). Digital Marketing Excellence: Planning, Optimizing and Integrating Online Marketing. https://doi.org/10.4324/9781003009498

Chang, P., & Chieng, M. (2006). Building consumer–brand relationship: A cross-cultural experiential view. Psychology & Marketing, 23(11), 927–959. https://doi.org/10.1002/mar.20140

Chen, Chiang, & Storey. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. MIS Quarterly, 36(4), 1165. https://doi.org/10.2307/41703503

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319. https://doi.org/10.2307/249008

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations. Journal of Marketing Research, 28(3), 307–319. https://doi.org/10.1177/002224379102800305

Erdem, T., & Swait, J. (1998). Brand Equity as a Signaling Phenomenon. Journal of Consumer Psychology, 7(2), 131–157. https://doi.org/10.1207/s15327663jcp0702_02

Fadlan Ihza Andika Widiyantoro, & Kuswati, R. (2024). Understanding the Influence of Brand Experience and Brand Satisfaction on Brand Loyalty: Mediated by Brand Love. Journal of Humanities and Social Sciences Studies, 6(2), 07–16. https://doi.org/10.32996/jhsss.2024.6.2.2

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39. https://doi.org/10.2307/3151312

Gupta, S., & Zeithaml, V. (2006). Customer Metrics and Their Impact on Financial Performance. Marketing Science, 25(6), 718–739. https://doi.org/10.1287/mksc.1060.0221

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. Journal of Marketing Theory and Practice, 19(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hammouri, H. M., Sabo, R. T., Alsaadawi, R., & Kheirallah, K. A. (2020). Handling Skewed Data: A comparison of two popular methods. Applied Sciences, 10(18), 6247. https://doi.org/10.3390/app10186247

Hevner, A., & Chatterjee, S. (2010). Design Science Research in Information Systems. In Design Research in Information Systems (Vol. 22, pp. 9–22). Springer US. https://doi.org/10.1007/978-1-4419-5653-8_2

Hofstede, G. (1980). Culture and Organizations. International Studies of Management & Organization, 10(4), 15–41. https://doi.org/10.1080/00208825.1980.11656300

Homburg, C., Koschate, N., & Hoyer, W. D. (2005). Do Satisfied Customers Really Pay More? A Study of the Relationship between Customer Satisfaction and Willingness to Pay. Journal of Marketing, 69(2), 84–96. https://doi.org/10.1509/jmkg.69.2.84.60760

Hong, S.-T., & Wyer, Jr., R. S. (1989). Effects of Country-of-Origin and Product-Attribute Information on Product Evaluation: An Information Processing Perspective. Journal of Consumer Research, 16(2), 175. https://doi.org/10.1086/209206

Jiang, F., Travaglione, T., Liu, L. X., & Li, J. (2021). When does the global mindset affect headquarters–subsidiary relationships? Journal of Business Research, 136, 523–542. https://doi.org/10.1016/j.jbusres.2021.08.002

Joshi, A., Kale, S., Chandel, S., & Pal, D. (2015). Likert scale: explored and explained. *British Journal of Applied Science & Technology*, *7*(4), 396–403. https://doi.org/10.9734/bjast/2015/14975

Kasali, F., Olaniyan, O., & Solomon, O. (2020). A framework for big data analytics in value creation.

Keller, K. L. (1993). Conceptualizing, Measuring, and Managing Customer-Based Brand Equity. Journal of Marketing, 57(1), 1–22. https://doi.org/10.1177/002224299305700101

Lee, P. K. C., Cheng, T. C. E., Yeung, A. C. L., & Lai, K. (2011). An empirical study of transformational leadership, team performance and service quality in retail banks. Omega, 39(6), 690–701. https://doi.org/10.1016/j.omega.2011.02.001

Lehrer, C., Wieneke, A., Vom Brocke, J., Jung, R., & Seidel, S. (2018). How Big Data Analytics Enables Service Innovation: Materiality, Affordance, and the Individualization of Service. Journal of Management Information Systems, 35(2), 424–460. https://doi.org/10.1080/07421222.2018.1451953

Liu, L., & Zhao, H. (2024). Research on consumers' purchase intention of cultural and creative products—Metaphor design based on traditional cultural symbols. PLOS ONE, 19(5), e0301678. https://doi.org/10.1371/journal.pone.0301678

Mahmudlu, K., & Muzaffarli, F. (2024). The Application of Big Data and Its Analytical Techniques in Behavioral Economics.

Man, M. (2016). Value of a brand name: Application of Aaker's Brand Equity Model.

Meyer, C., & Schwager, A. (2007). Understanding Customer Experience. Harvard Business Review, 85, 116–126, 157.

Nunnally, J. C. (1978). An Overview of Psychological Measurement. In Clinical Diagnosis of Mental Disorders (pp. 97–146). Springer US. https://doi.org/10.1007/978-1-4684-2490-4_4

Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. Journal of Marketing Research, 17(4), 460–469. https://doi.org/10.1177/002224378001700405

Perera, W. K. R., Dilini, K. A., & Kulawansa, T. (2018). A Review of Big Data Analytics for Customer Relationship Management. 2018 3rd International Conference on Information Technology Research (ICITR), 1–6. https://doi.org/10.1109/ICITR.2018.8736131

Purwanto, A., & Prayuda, R. (2024). The Role of Brand Image, Brand Experience, Influencer Marketing and Purchase Interest on Consumer Purchasing Decisions of Handphone.

Rajasa, E., Manap, A., Doddy, P., Ardana, P., Yusuf, M., Bangsa, U., Jayabaya, U., Rai, U., Bandung, S., & Medan, P. (2023). Literature Review: Analysis of Factors Influencing Purchasing Decisions, Product Quality and Competitive Pricing.

Ramlall, I. (2016). Applied Structural equation modelling for researchers and practitioners. https://doi.org/10.1108/9781786358820

Reddy, P., Chaudhary, K., & Hussein, S. (2023). A digital literacy model to narrow the digital literacy skills gap. Heliyon, 9(4), e14878. https://doi.org/10.1016/j.heliyon.2023.e14878

Reisinger, Y., & Mavondo, F. (2007). Structural Equation Modeling: Critical Issues and New Developments. Journal of Travel & Tourism Marketing, 21(4), 41–71. https://doi.org/10.1300/J073v21n04_05

Romaniuk, J., & Sharp, B. (2003). Measuring brand perceptions: Testing quantity and quality. Journal of Targeting, Measurement and Analysis for Marketing, 11(3), 218–229. https://doi.org/10.1057/palgrave.jt.5740079

Salhab, H. A., Al-Amarneh, A., Aljabaly, S. M., Zoubi, M. M. A., & Othman, M. D. (2023). The impact of social media marketing on purchase intention: The mediating role of brand trust and image. International Journal of Data and Network Science, 7(2), 591–600. https://doi.org/10.5267/j.ijdns.2023.3.012

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial Least Squares Structural Equation Modeling. In Handbook of Market Research (pp. 1–40). Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-1
Shavitt, S., & Barnes, A. J. (2019). Culture and the consumer journey. Journal of Retailing, 96(1), 40–54. https://doi.org/10.1016/j.jretai.2019.11.009
Shinija, Mrs.N.Adlin. (2023). NON-PROBABILITY SAMPLING.
Shneif, M. (2015). Principles and Practice of Structural Equation Modeling Rex B. Kline.
Singhal, A., & Rogers, E. (2012). Entertainment-Education: A Communication Strategy for Social Change. https://doi.org/10.4324/9781410607119
Toldos-Romero, M. D. L. P., & Orozco-Gómez, Ma. M. (2015). Brand personality and purchase intention. European Business Review, 27(5), 462–476. https://doi.org/10.1108/EBR-03-2013-0046
Venkatesh, Thong, & Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157. https://doi.org/10.2307/41410412
Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. Journal of Retailing, 85(1), 31–41. https://doi.org/10.1016/j.jretai.2008.11.001
Wang, X., & Yang, Z. (2011). The impact of brand credibility and brand personality on purchase intention: An empirical study in China. In Advances in International Marketing (Vol. 21, pp. 137–153). Emerald Group Publishing Limited. https://doi.org/10.1108/S1474-7979(2011)0000021009
Wijaya, I. W. K., Rai, A. a. G., & Hariguna, T. (2019). The impact of customer experience on customer behavior intention use in social media commerce, an extended expectation confirmation model: An empirical study. Management Science Letters, 2009–2020. https://doi.org/10.5267/j.msl.2019.7.005
Yi, M., Chen, M., & Yang, J. (2024). Understanding the self-perceived customer experience and repurchase intention in live streaming shopping: Evidence from China. Humanities and Social Sciences Communications, 11(1), 202. https://doi.org/10.1057/s41599-024-02690-6
Yoo, B., Donthu, N., & Lee, S. (2000). An Examination of Selected Marketing Mix Elements and Brand Equity. Journal of the Academy of Marketing Science, 28(2), 195–211. https://doi.org/10.1177/0092070300282002
Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1988). Communication and Control Processes in the Delivery of Service Quality. Journal of Marketing, 52(2), 35–48. https://doi.org/10.1177/002224298805200203

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