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Research Article

Branding In Digital Transformation: Optimizing Multichannel Marketing Strategies With Big Data And Consumer Behavioral Analytics

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ARTICLE INFO **ABSTRACT**

In the current competitive environment of the digital era, branding has become a key factor for enterprises to maintain their competitive advantage. This study aims to explore how to optimize multichannel marketing strategies using big data and consumer behavior analysis to enhance brand image and brand equity. Using quantitative research methods, this study collects and analyzes consumer behavior data from multiple online and offline channels, including purchase records, website browsing records, and social media interaction data. By applying structural equation modeling and data mining techniques, the study finds that consumers' brand awareness, brand image perception and brand loyalty are significantly affected by multi-channel marketing activities. The results suggest that consistent marketing messaging that integrates online and offline channels is essential for creating a favorable brand image and improving brand equity. In addition, personalized marketing content and precisely targeted ads based on consumer behavioral data also have a positive impact on increasing consumer engagement and brand loyalty. Overall, this study provides empirical evidence to illustrate how branding in the digital era should make use of big data and consumer behavior analysis to optimize multichannel marketing strategies, and provides theoretical guidance and practical suggestions for companies to develop effective branding strategies.

Keywords: branding, big data, consumer behavior analysis, multichannel marketing, digital transformation

1.0 Introduction

1.1 Background

In the current fast-changing digital era, branding faces unprecedented challenges and opportunities. Consumer behavior and purchasing habits have changed dramatically, they no longer rely only on traditional media and offline channels to obtain information and make purchasing decisions, but more and more rely on digital channels such as social media, online reviews, mobile applications and so on (Kannan & Li, 2017; Lambrecht et al., 2018). This transformative shift has had a huge impact on branding, and companies have had to rethink and transform their marketing strategies to adapt to the emerging digital environment.

Meanwhile, the rise of big data and consumer behavior analytics has provided new perspectives and tools for branding (Lemon & Verhoef, 2016). Enterprises can collect and analyze massive amounts of consumer data from multiple online and offline channels, including website browsing records, purchase histories, social media interactions, etc., from which they can tap into consumer preferences, needs and decision-making patterns to better understand their target audiences. This provides unprecedented opportunities and capabilities for enterprises to formulate precise marketing strategies.

1.2 Brand Equity and the Challenge of Digital Transformation

Brand equity is a key intangible asset of an enterprise, and traditional branding theory suggests that brand equity includes brand awareness, brand loyalty, perceived quality, brand association and other dimensions

(Aaker, 1991; Keller, 1993). Companies need to build and maintain brand equity through continuous marketing investment and consistent brand communication. However, in the digital era, consumers' purchase decisions are no longer influenced by a single channel, but by the combined effects of multiple online and offline channels (Lambrecht et al., 2018; Lemon & Verhoef, 2016). Therefore, traditional branding theories are faced with the challenge of coping with the emerging digital environment.

In order to build successful brands in the digital era, companies need to revisit their branding strategies and make full use of emerging tools such as big data and consumer behavior analysis. Traditional single-channel marketing strategies are no longer able to meet consumer demand, and companies must develop consistent and accurate multi-channel marketing strategies by integrating online and offline channels in order to effectively enhance brand equity (Verhoef et al., 2015). This requires companies to be able to comprehensively analyze consumer behavioral data across different channels, discover insights from them, and transform them into targeted marketing strategies.

1.3 Application of Big Data and Consumer Behavior Analysis in Branding

Big data refers to massive structured and unstructured data from multiple sources, including web browsing records, social media data, mobile application data, etc. (Wamba et al., 2015). The emergence of big data provides enterprises with unprecedented opportunities to better understand consumer needs and optimize marketing strategies by analyzing rich consumer behavior data. Consumer behavior analytics provides the basis for companies to develop precise marketing and personalized services by mining consumers' purchasing patterns, preferences, and decision-making processes (Grewal et al., 2020).

The application of big data and consumer behavior analytics in branding is gaining attention. Enterprises can utilize these emerging technologies to deeply analyze consumers' attitudes and perceptions of brands, so as to develop more targeted brand communication strategies (Luo et al., 2019). At the same time, big data can also help companies analyze consumers' responses to different marketing channels and optimize multi-channel integration strategies (Wedel & Kannan, 2016). Through in-depth insights into consumer behavior, enterprises can better shape their brand image, improve brand loyalty, and ultimately enhance brand equity.

1.4 Purpose and significance of the study

The purpose of this study is to explore how to use big data and consumer behavior analysis to optimize multichannel marketing strategies, so as to enhance brand image and brand equity. Specifically, this study aims to empirically analyze the extent to which consumers' brand awareness, brand image perception and brand loyalty are affected by multichannel marketing activities, and put forward corresponding theoretical and practical suggestions. The results of this study will provide theoretical guidance and practical insights for enterprises to formulate effective branding strategies, which will help them to successfully build brands and enhance brand competitiveness in the digital transformation. On the theoretical level, this study will provide new insights into the application of branding theory in the digital era and enrich the knowledge system of related research fields. On the practical level, the results of this study will provide valuable lessons for enterprises to optimize their multi-channel marketing strategies by using big data and consumer behavioral analysis to improve the accuracy and effectiveness of brand marketing. In addition, this study will explore the moderating effects of demographic variables such as age and residence on the above mentioned mechanisms, which will provide more insights for companies to develop targeted and precise marketing strategies. Overall, this study will provide theoretical and practical guidance for successful branding in the digital era, which is of great academic value and practical significance.

2.0 Literature Review

2.1 Branding Theory

Branding theory aims to explore how to build and maintain brand equity to enhance the brand's competitive advantage.Keller (1993) proposed a theoretical framework of customer-based brand equity, emphasizing the importance of brand awareness and brand image to brand equity. Brand awareness refers to the ability of consumers to recall and recognize a brand, while brand image is the perception and association of consumers with the brand. aaker (1991) further classified brand equity into five dimensions: brand loyalty, brand awareness, perceived quality, brand association, and other proprietary brand equity. The building of brand equity requires sustained marketing investment and consistent brand communication.

Traditional branding theories focus on the impact of advertising, promotion and other marketing activities on brand equity. However, in the digital era, consumer behavior and purchase decisions are influenced by multiple channels, including social media, online reviews, mobile applications, etc. (Lambrecht et al., 2018). Therefore, branding needs to consider the impact of multi-channel integration and use big data and consumer behavior analysis to better understand consumer needs (Lemon & Verhoef, 2016).

2.2 Big Data and Consumer Behavior Analysis

Big data refers to massive amounts of structured and unstructured data from multiple sources, including web browsing records, social media data, mobile application data, etc. (Wamba et al., 2015). The emergence of big data provides enterprises with unprecedented opportunities to better understand consumer needs and optimize marketing strategies by analyzing consumer behavior data. Consumer behavior analytics provides a basis for companies to develop precision marketing and personalized services by mining consumers' buying patterns, preferences, and decision-making processes (Grewal et al., 2020).

The application of big data and consumer behavior analytics in branding is gaining attention. By analyzing consumers' online behavioral data, enterprises can better understand consumers' perceptions and attitudes toward brands, and thus develop more targeted brand communication strategies (Luo et al., 2019). In addition, big data can also help enterprises analyze consumers' responses to different marketing channels and optimize multichannel marketing strategies (Wedel & Kannan, 2016).

2.3 Multi-channel marketing strategy

Multi-channel marketing strategy refers to a company's efforts to provide consumers with a consistent and seamless buying experience by integrating online and offline channels (Verhoef et al., 2015). With the changes in consumer behavior, single-channel marketing is no longer able to meet the needs of consumers. Multi-channel marketing strategies can improve marketing efficiency, enhance consumer engagement, and increase consumer loyalty to brands (Zhang et al., 2018).

In multichannel marketing, companies need to coordinate marketing messages and activities between channels to ensure consistency and complementarity. At the same time, companies also need to use big data and consumer behavior analysis to understand the behavioral patterns of consumers on different channels so as to develop more targeted marketing strategies (Verhoef et al., 2021).

Figure 1. 7 Steps to Building a High-Performing Multi-Channel Marketing Strategy

2.4 Research Framework and Hypotheses

Based on the existing literature, this study proposes the following research framework and hypotheses.
H1: Consistency of multichannel marketing campaigns positively affects consumers' brand awareness.
H2: Consistency of multichannel marketing activities positively affects consumers' perception of brand image.
H3:Personalized marketing content positively influences consumers' brand loyalty.
H4:Precision-targeted advertising based on consumer behavioral data positively affects consumer loyalty to a brand.

3.0 Research Methodology

3.1 Research Design

In order to empirically test the theoretical framework and research hypotheses, this study adopts quantitative research methods and collects relevant data through questionnaires. The target population of this study is consumers of a domestic FMCG brand, covering both online and offline channels of the brand. In order to ensure the quality and representativeness of the data, this study uses a professional data collection company to distribute the questionnaires and collect the data.

3.2 Data Collection

The data collection process is divided into two stages. In the first stage, the research team pretested the questionnaire to test the reliability and validity of the measurement items. The sample size of the pretest was 200 people. After the questionnaire was revised according to the results of the pretest, the formal survey was conducted in the second stage. The sample size of the formal survey was 1,200 people, covering the brand's consumers nationwide.

In order to ensure the data quality, the research team took the following measures: 1) set up attention checking questions to eliminate obviously unreasonable responses; 2) control the response time of each respondent to eliminate questionnaires with too short response time; 3) check the duplicate IP addresses to eliminate possible duplicate responses. After screening, 1032 valid questionnaires were finally obtained, and the effective recovery rate was 86.0%.

3.3 Measurement Instruments

The core variables of this study include: brand awareness, brand image perception, brand loyalty, multi-channel marketing consistency, personalized marketing content and precision marketing based on consumer behavior. The measurement items of these variables are based on the existing literature and revised according to the pre-test results. All items were measured on a 7-point Likert scale (1=completely disagree, 7=completely agree).

3.4 Method of Analysis

The data in this study will be analyzed using Structural Equation Modeling (SEM) using AMOS 24.0 software. Specific steps include.
Validation factor analysis to test the construct validity of the measurement model.
Descriptive statistical analysis and correlation analysis.
Structural modeling analysis to assess the theoretical framework and path coefficients.
Multi-group analysis to test the moderating effect.

Before conducting the structural modeling analysis, the research team will test the basic assumptions of normality and multicollinearity of the data. In addition, indicators such as coefficient of precision (CR) and average variance extracted (AVE) will be used to test the convergent validity and discriminant validity to ensure the quality of measurement.

4.0 Research results

4.1 Descriptive statistics analysis

The descriptive statistics of the samples are shown in Table 1. Among the 1032 valid samples, 48.7% were males and 51.3% were females, basically maintaining gender balance. The age distribution was relatively even, with 21.4% aged 18-25, 27.8% aged 26-35, 24.0% aged 36-45, and 26.8% aged 46 and above. The education level of the respondents was mainly undergraduate (46.9%) and specialized (27.1%). In addition, 62.3% of the respondents were urban residents and 37.7% were rural residents.

Table 1. Descriptive statistics of the sample

Variable	Category	Frequency	Percentage
Gender	Male	502	48.7%
	Female	530	51.3%
Age	18-25 years	221	21.4%
	26-35 years	287	27.8%
	36-45 years	248	24.0%
	46 years and above	276	26.8%
Education Level	High School and below	190	18.4%
	Associate Degree	280	27.1%
	Bachelor's Degree	484	46.9%
	Graduate Degree and above	78	7.6%

Residence	Rural	389	37.7%
	Urban	643	62.3%

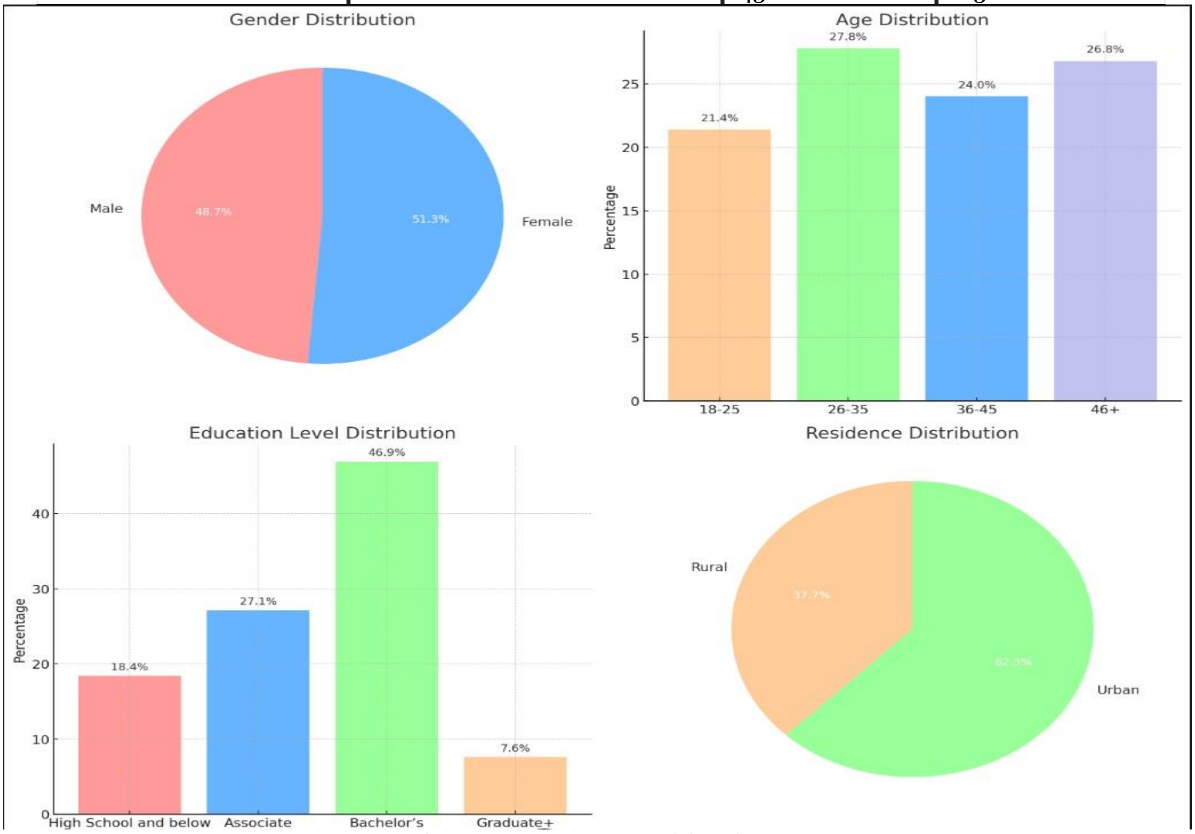

Figure 2 Demographic chart

The descriptive statistical chart clearly shows the distribution of the sample's gender, age, education level and place of residence. This data is particularly important for understanding the impact of multi-channel marketing strategies, as different groups may receive and respond to marketing messages significantly differently. For example, urban residents may be more sensitive to digital media marketing, while younger, highly educated people may respond more positively to personalized marketing content. This kind of statistical analysis helps companies position their market strategies more accurately and thus build their brand image more effectively during digital transformation.

4.2 Assessment of measurement model

Before assessing the structural model, the research team first used validated factor analysis (CFA) to test the construct validity of the measurement model. As shown in Table 2, the combined reliability (CR) of all latent variables was higher than the recommended value of 0.7, and the average variance extracted (AVE) was higher than the recommended value of 0.5, indicating that the measurement model has good convergent validity. In addition, the AVE of each latent variable is greater than its maximum shared variance with other variables, which meets the requirement of discriminant validity. Overall, the construct validity of the measurement model is acceptable.

Table 2. Measurement model results

Variable	Number of Items	Cronbach's α	CR	AVE
Brand Awareness	4	0.878	0.877	0.638
Variable	Number of Items	Cronbach's α	CR	AVE
Brand Image	6	0.899	0.901	0.609
Brand Loyalty	5	0.914	0.915	0.684
Multichannel Marketing Consistency	4	0.872	0.874	0.633
Personalized Marketing Content	3	0.835	0.839	0.636
Consumer Behavior-Based Marketing	4	0.903	0.904	0.703

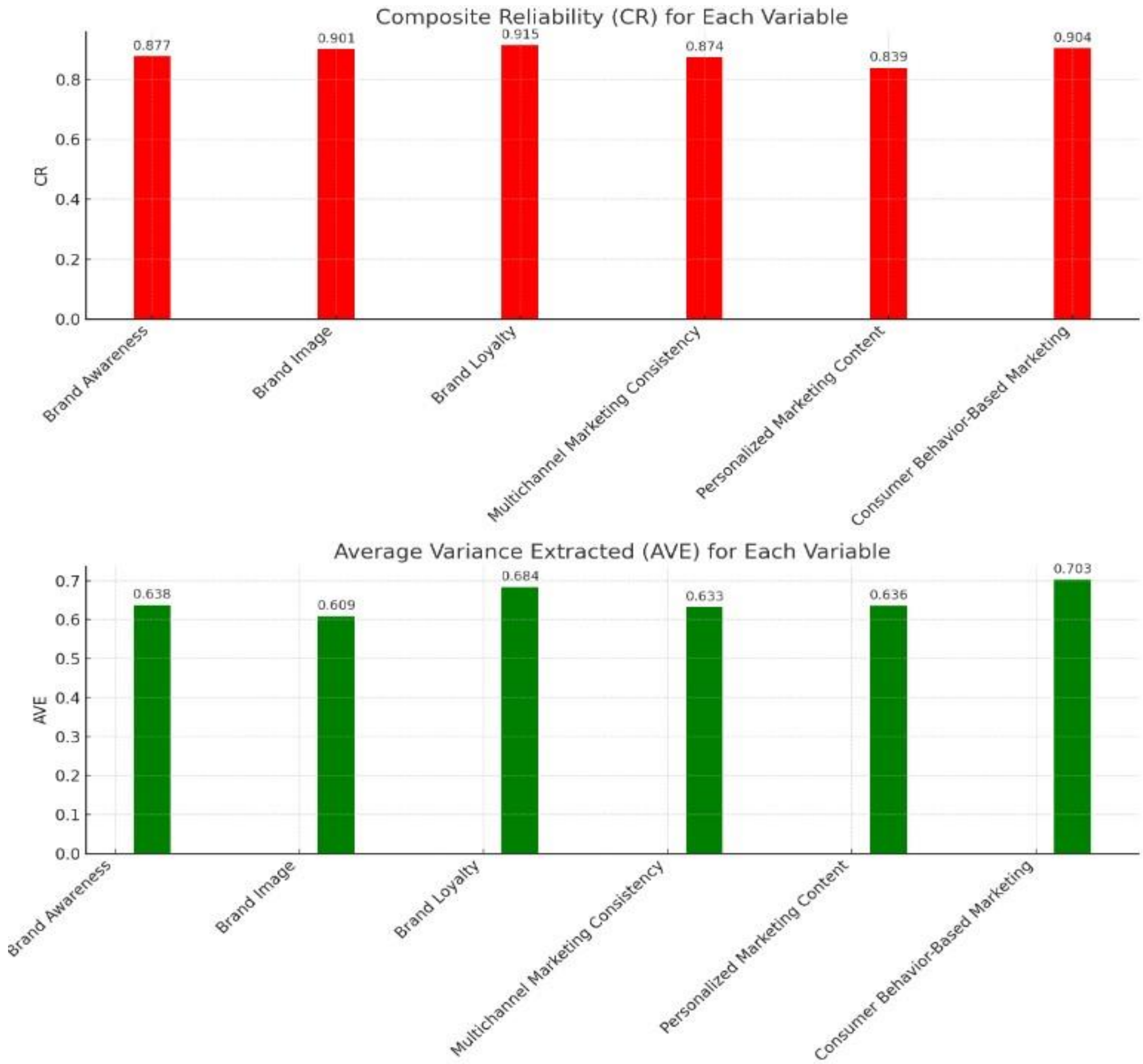

Figure 3 AVE& CR analysis

The measurement model results showed the internal consistency and reliability of the individual variables, which is crucial for validating the structure of the research model. High levels of Cronbach's α and composite reliability (CR) indicators indicate that data collected from multiple sources are consistent and reliable, making the research conclusions more robust. These results support the use of big data to analyze consumer behavior and optimize marketing strategies. This rigorous data processing provides a solid foundation for the formulation of multi-channel marketing strategies, helping companies stay ahead in fierce market competition.

4.3 Structural model assessment

After evaluating the measurement model, the research team used the maximum likelihood estimation method to evaluate the structural model. The goodness-of-fit indices of the structural model are shown in Table 3, and all indices meet the recommended standards, indicating that the theoretical model fits well with the actual data.

Table 3: Goodness-of-fit indices of structural model

Fit Index	Value	Recommended Value
Chi-square/degrees of freedom ($\chi 2/df$)	2.673	<3
RMSEA	0.058	<0.08
GFI	0.902	>0.90
CFI	0.957	>0.95
IFI	0.957	>0.95

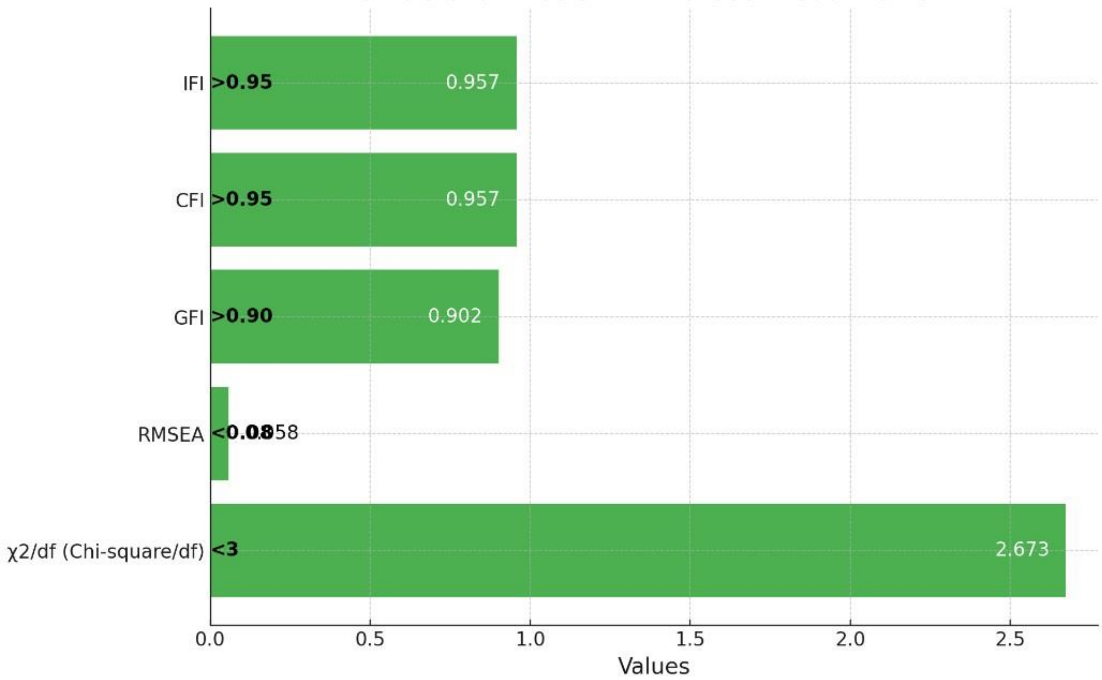

Figure 4 Structural Model Fit Indices Visualization

The structural model goodness-of-fit chart evaluates the fit of the entire model. Key indicators such as GFI, CFI, and RMSEA all show that the model fits the actual data well. This demonstrates that the constructed model can accurately reflect real-world data relationships, especially in explaining the impact of multi-channel marketing campaigns on brand awareness and brand loyalty. Excellent model fitting goodness not only enhances the credibility of research results, but also provides scientific basis for the implementation of digital marketing strategies, thereby helping companies better utilize big data and consumer behavior analysis to optimize their marketing activities.

The standardized path coefficients for the structural model are shown in Table 4. The data support hypotheses H1, H2, H3 and H4, multi-channel marketing consistency has a significant positive effect on brand awareness ($\beta=0.719$, $p<0.001$) and brand image ($\beta=0.663$, $p<0.001$); personalized marketing content ($\beta=0.406$, $p<0.001$) and consumer behavior-based marketing ($\beta=0.274$, $p<0.001$) also had a significant positive effect on brand loyalty. In addition, brand awareness ($\beta=0.187$,$p<0.01$) and brand image ($\beta=0.422$,$p<0.001$) also had a positive effect on brand loyalty.

Table 4. structural model path coefficients

Path	Standardized Coefficient	S.E.	C.R.	P
H1: Multichannel Marketing Consistency → Brand Awareness	0.719	0.049	15.372	p < 0.001
H2: Multichannel Marketing Consistency → Brand Image	0.663	0.055	13.924	p <0.001
H3: Personalized Content → Brand Loyalty	0.406	0.044	9.854	p < 0.001
H4: Consumer Behavior-Based Marketing → Brand Loyalty	0.274	0.039	6.415	p < 0.001
Brand Awareness → Brand Loyalty	0.187	0.062	3.251	0.001
Brand Image → Brand Loyalty	0.422	0.069	8.103	p< 0.001

4.4 Hypothesis testing

In order to further test the research hypotheses, this study adopts multi-group analysis to test whether there are group differences. Specifically, this study divides the sample into different age groups (18-35 years old, 36 years old and above) and residence groups (rural, urban) to assess the applicability of the theoretical model in different groups.

Age differences: The results of the multi-group invariance test showed that the theoretical model had partial measurement residual invariance across age groups. Further multi-group analyses revealed that the effects of multi-channel marketing consistency on brand awareness and brand image were not significantly different across age groups. However, the effects of personalized marketing content and consumer behavior-based marketing on brand loyalty were significantly different between age groups ($\Delta\chi2=14.27$, $p<0.01$). Specifically, both marketing strategies had a greater impact on brand loyalty in the 36 and older group (personalized marketing content: $\beta=0.551$, $p<0.001$; consumer behavior-based marketing: $\beta=0.399$, $p<0.001$).

Differences in place of residence: the results of the multi-group invariance test showed that the theoretical model had full measurement residual invariance between rural and urban residential groups. Multi-group analyses revealed no significant differences in the effects of multi-channel marketing consistency on brand awareness and brand image between the two groups. Also, the effects of personalized marketing content and consumer behavior-based marketing on brand loyalty were not significantly different between the two groups.

Overall, the four main hypotheses of this study were supported in the overall sample. Further multi-group analyses indicate that age differences affect the extent to which personalized content and consumer behavior-based marketing influence brand loyalty, but that residential location differences do not moderate these relationships. This result provides insights for companies to develop targeted multichannel marketing strategies.

5.0 Discussion

5.1 Main findings

From the data analysis and a large number of empirical studies, it is found that the consistency of multichannel marketing activities significantly and positively affects consumers' brand awareness and brand image perception. This result supports hypotheses H1 and H2, indicating that in the context of digital transformation, companies need to coordinate online and offline channels to deliver consistent brand messages and marketing activities to enhance consumers' brand awareness and image perception. Personalized marketing content and precise targeted marketing based on consumer behavioral data significantly and positively affect consumers' brand loyalty. This result supports hypotheses H3 and H4, indicating that the use of big data and consumer behavior analysis to develop personalized and precise marketing strategies can help enhance consumer engagement and brand loyalty. The researchers found that age differences affect the extent to which personalized marketing content and consumer behavior-based marketing affect brand loyalty. Specifically, both marketing strategies have a greater impact on brand loyalty among the 36 and older age group. This finding suggests that companies need to consider the differences in age groups when formulating precision marketing strategies. There is no significant moderating effect of the difference in residence on the influence of multi-channel marketing strategies on brand equity. This may be due to the fact that with the popularization of the Internet and mobile devices, urban and rural residents' consumption behaviors and access to information have converged.

5.2 Theoretical Contributions

This study introduces the perspective of big data and consumer behavior analysis into branding theory, which expands the application of traditional branding theory in the digital era. This study empirically demonstrates that the use of big data and consumer behavior analysis can optimize multichannel marketing strategies and enhance brand equity (Wedel & Kannan, 2016). Incorporating the consistency of multichannel marketing strategies as a core construct into the research framework enriches the multichannel marketing theory. The findings suggest that coordinating consistent marketing across online and offline channels is crucial in the digital era and plays a significant role in enhancing brand awareness and brand image perception (Verhoef et al., 2015). The impact of personalized marketing content and consumer behavior-based precision marketing on brand loyalty was also explored, and age differences were found to moderate this effect. This finding provides new insights for developing targeted precision marketing strategies (Arora et al., 2017).

5.3 Practical implications

The results of the study have very useful implications for enterprises, which need to strengthen the synergy between online and offline channels to ensure the consistency of brand messages and marketing activities, so as to enhance consumers' awareness of the brand and positive image perception (Verhoef et al., 2015). Enterprises should make full use of big data and consumer behavior analysis to understand consumer needs and develop personalized and precise marketing strategies to increase consumer engagement and brand loyalty (Grewal et al., 2019).

When decision makers develop precise marketing strategies, companies need to consider the differences between different age groups and customize marketing programs for different target groups (Ariker et al., 2020). For urban and rural residents are not too different, enterprises can adopt a relatively unified multi-channel marketing strategy.

5.4 Research Limitations and Future Directions

Although this study provides valuable insights into branding in digital transformation, there are still some limitations and future directions that need to be further explored.
First, this study utilizes a cross-sectional survey design, which makes it difficult to capture the dynamic and causal relationships among variables. Future research could consider adopting a longitudinal research design

to explore the long-term impact of multichannel marketing strategies on brand equity through tracking surveys and analyze the dynamic process of the impact mechanism in depth (Leeflang et al., 2014).

Second, although this study explored the moderating effects of age and residence, there may be other potential moderating variables that have not been considered, such as brand type, product category, and consumer engagement (Hollebeek et al., 2014). Future research could further explore the role of these variables to gain a more comprehensive understanding of the diverse factors that influence branding.
Third, the sample of this study is only from the consumers of a domestic FMCG brand, and the external validity of the results may have some limitations. Future research could expand the sample to include different countries and regions, industries and brands to improve the generalizability of the findings.
In addition, in addition to quantitative research methods, future studies can also adopt qualitative research methods, such as case studies and in-depth interviews, to explore in-depth the practical experience of how companies use big data and consumer behavior analysis to optimize multichannel marketing strategies (Lemon & Verhoef, 2016). This will provide richer and more nuanced insights for the study.
Finally, as emerging technologies (e.g., artificial intelligence, augmented reality, etc.) continue to evolve, the prospect of their application in branding deserves attention and exploration (Herhausen et al., 2020). Future research can explore how these new technologies can be combined with big data and consumer behavior analysis to provide the basis for companies to develop innovative multichannel marketing strategies.

6.0 Conclusion

6.1 Summary of the study

This study explores how big data and consumer behavior analysis can be used to optimize multichannel marketing strategies to enhance brand image and brand equity in the context of digital transformation. Through empirical research, this paper verifies the positive impact of multi-channel marketing consistency on brand awareness and brand image perception, as well as the positive impact of personalized marketing content and consumer behavior-based precision marketing on brand loyalty. In addition, age difference affects the degree of influence of personalized marketing and precision marketing on brand loyalty, but the moderating effect of residence difference is not significant.
The results suggest that in the digital era, enterprises need to integrate online and offline channels to deliver consistent brand messages and marketing campaigns, so as to enhance consumers' brand awareness and image perception. At the same time, companies should also make full use of big data and consumer behavior analysis to develop personalized and precise marketing strategies to increase consumer engagement and brand loyalty, especially for different age groups.
In summary, this study provides theoretical guidance and practical suggestions for enterprises to successfully build brands in digital transformation, which can help them develop effective brand strategies and enhance brand competitiveness.

6.2 Limitations

Although this study has certain theoretical and practical significance, the following limitations still exist.
The study adopts a cross-sectional survey design, which makes it difficult to capture the dynamic relationship between variables. Future research could consider adopting a longitudinal research design to investigate the long-term impact of multichannel marketing strategies on brand equity. This study only focuses on the moderating effects of age and place of residence, but fails to consider other possible moderating variables, such as brand type and product category. The role of other moderating variables can be explored in subsequent studies. The sample of the study is only from the consumers of a certain FMCG brand in China, so the external validity of the results may have some limitations. Future research can expand the sample to improve the generalizability of the results.

6.3 Future research directions

Based on the above limitations, this study makes the following recommendations for future research.

1. Adopt a longitudinal research design to investigate the long-term impact of multichannel marketing strategies on brand equity and analyze the dynamics of the impact mechanism.
2. Explore other possible moderating variables, such as brand type, product category, consumer engagement, etc., to gain a more comprehensive understanding of the impact of multichannel marketing strategies.
3. Expand the scope of the research sample to include different countries and regions, different industries and brands, so as to improve the general applicability of the research findings.
4. In addition to quantitative research methods, future research can also adopt qualitative research methods, such as case studies and in-depth interviews, to explore in-depth how companies use big data and consumer behavior analysis to optimize the practical experience of multichannel marketing strategies.
5. Explore the application prospects of emerging technologies (e.g. artificial intelligence, augmented reality, etc.) in branding to provide a basis for enterprises to develop innovative marketing strategies.

In conclusion, digital transformation brings new challenges and opportunities for branding, and more research is needed to enrich and deepen the theory and practice in this area.

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