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Research Article

Confirmatory Factor Analysis of the Relationship Between Digital Marketing and Consumer Attitudes

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ARTICLE INFO	ABSTRACT
	Digital marketing has become a dominant force in shaping consumer attitudes, influencing perceptions, engagement, and purchasing decisions. With the rise of personalized advertising, social media campaigns, and search engine marketing, understanding the underlying structure of consumer attitudes toward digital marketing is essential. This study employs Confirmatory Factor Analysis (CFA) to examine the factor structure of consumer responses to digital marketing efforts, focusing on key constructs such as brand trust, perceived value, engagement, and purchase intention. A quantitative survey was conducted among a diverse consumer base, collecting data through a structured questionnaire using Likert-scale measurements. The CFA model was tested using AMOS, assessing factor loadings, model fit indices, reliability, and validity. Key model fit indicators, including Chi-square, Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA), were analyzed to determine the robustness of the proposed framework. The findings confirm the significance of digital marketing in shaping consumer attitudes and provide empirical evidence supporting the role of trust, engagement, and perceived value in influencing purchase intent.

Introduction

In today's digital landscape, marketing has evolved significantly, shaping consumer attitudes and behaviors in unprecedented ways. Digital marketing strategies, including social media marketing, search engine optimization (SEO), content marketing, and personalized advertising, have transformed the way businesses engage with consumers. These strategies leverage data-driven insights to create targeted campaigns that influence consumer perceptions, preferences, and purchasing decisions. As consumer attitudes are crucial in determining the success of marketing initiatives, understanding their underlying structure is essential. Confirmatory Factor Analysis (CFA) provides a robust statistical approach to examining the factor structure of consumer attitudes in response to digital marketing. By applying CFA, researchers can validate theoretical models and identify key dimensions influencing consumer perceptions, such as trust, engagement, brand loyalty, and purchase intent. This analytical technique ensures a comprehensive understanding of how digital marketing efforts shape consumer psychology and decision-making.
This study aims to investigate the factor structure underlying the relationship between digital marketing and consumer attitudes using CFA. By analyzing empirical data, the study seeks to confirm whether specific latent constructs—such as brand trust, perceived value, online engagement, and purchase intention—adequately explain consumer responses to digital marketing efforts. The findings of this research will contribute to both academic literature and practical marketing strategies, helping businesses refine their digital marketing tactics for maximum consumer engagement. Moreover, identifying the key factors that drive consumer attitudes will enable marketers to optimize their communication strategies, foster brand loyalty, and enhance overall customer experience. As digital marketing continues to evolve, a deeper understanding of its impact on consumer attitudes through empirical methods like CFA becomes increasingly critical for businesses aiming to stay competitive in the digital economy.

Methodology

This study employs Confirmatory Factor Analysis (CFA) to examine the factor structure underlying the relationship between digital marketing and consumer attitudes. CFA is a statistical technique used to validate the construct validity of a theoretical model by assessing the relationships between observed variables and their underlying latent factors. The research follows a quantitative approach, utilizing survey data collected from a diverse group of consumers who engage with digital marketing channels such as social media, email marketing, search engine advertisements, and influencer marketing.
The data collection process involves a structured questionnaire with Likert-scale items designed to measure key constructs such as brand trust, perceived value, engagement, and purchase intention. A random sampling technique is employed to ensure a representative sample of consumers across different demographics. AMOS to test the model fit and assess factor loadings, reliability, and validity. Goodness-of-fit indices, including Chi-square, Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA), are used to determine the model's suitability. The results of this analysis will help confirm whether the hypothesized factor structure accurately explains consumer attitudes toward digital marketing, contributing to both theoretical understanding and practical applications in digital marketing strategy.

Data analysis

The number of responses required per item in a questionnaire for validation in research studies varies depending on the type of study and the specific research question being investigated. However, a general rule of thumb is that a minimum of five to ten responses per item is required for reliable validation purposes (Cohen et al., 2016). This rule of thumb is based on the principle of the Law of Large Numbers, which suggests that the larger the sample size, the more representative it is of the population being studied. By having multiple responses per item, researchers can ensure that the results are consistent and reliable. A study by Henson et al. (2019) found that having at least five responses per item was essential for the validation of a measure of cognitive flexibility in children. Similarly, a study by Huang et al. (2020) found that using a sample of at least 150 participants and having a minimum of five responses per item was necessary for adequate validation of a questionnaire measuring nursing students' perceptions of clinical learning environments.

According to Streiner and Norman (2015), a minimum of five responses per item is recommended for exploratory factor analysis, while ten responses per item are recommended for confirmatory factor analysis. Similarly, DeVellis (2017) suggests a minimum of five responses per item for initial scale development and a minimum of ten responses per item for scale validation. Recent research studies have also supported these recommendations. For example, in a study by Furr et al. (2018), the authors used confirmatory factor analysis to validate a measure of emotion regulation and found that a minimum of ten responses per item was required to achieve reliable results. In another study by van der Meer et al. (2020), the authors used exploratory factor analysis to validate a measure of social anxiety and found that a minimum of five responses per item was required to achieve reliable results. Therefore, a minimum of five to ten responses per item is recommended for validation purposes in questionnaire-based research studies, depending on the type of analysis being conducted. Researchers should also consider the specific research question being investigated and aim to collect as many responses as possible to increase the reliability of their results.

Keeping in view the objective of the present study, we have extracted varied yet important factors and the confirmatory factor analysis was applied. So, in the entire analysis, three software were used i.e., MS excel, SPSS and AMOS. Author(s) have very carefully examined and met the assumption of EFA and CFA. The first and foremost step was to check the data normality. Therefore, this process was started with identifying outliers. Further, Outliers are defined by Hair et al. (2010) as data that vary noticeably from other observations on one or more identifiable characteristics or variables. Outliers are numbers that deviate greatly from the average of the statistics. Values are deemed "outliers" in a discretionary manner. We used the boxplot to identify the outliers. Boxplot is a graphical display of the data that shows. Therefore, the data set were checked for outliers and the premise of normality was evaluated using the proper statistical tools, as will be described subsequently, before moving on to the following parametric tests

Testing the Assumption of Normality

The assumption of normality was evaluated for each of the five underlying research constructs. According to the premise of normality, the mean sampling distribution or the distribution of means among samples should be considered normal. The data's normality is evaluated through both graphic and statistical techniques. Both skewness and kurtosis are characteristics of normality.

Table:1 Factor structure for Relationship Between Digital Marketing and Consumer Attitudes

	Variables	Factor Loadings	Mean	Std. Deviation
1. Digital Marketing Techniques	DMT1	.903	4.08	1.068
	DMT2	.811	4.06	.976
	DMT3	.820	4.13	.933
	DMT4	.896	4.16	1.061
	DMT5	.932	3.94	1.088
	DMT6	.926	4.12	1.102
	DMT7	.790	3.47	.881
	DMT8	.948	3.64	.997
	DMT9	.885	3.69	1.046
	DMT10	.858	3.75	1.004
2. Consumer Attitudes towards a Brand/Product	CAB1	.901	3.57	.995
	CAB2	.898	3.74	1.092
	CAB3	.954	3.69	1.055
	CAB4	.914	3.52	1.108
	CAB5	.834	3.54	1.142
	CAB6	.773	3.96	1.121
	CAB7	.810	3.83	1.167
	CAB8	.857	3.95	1.061
	CAB9	.759	4.05	.972
	CAB10	.852	4.01	1.095
3. Factors Affecting Consumer Attitudes Towards Digital Marketing	FACA1	.820	3.69	1.194
	FACA2	.841	4.09	1.021
	FACA3	.839	3.83	1.046
	FACA4	.853	4.08	.922
	FACA5	.820	4.03	.916
	FACA6	.785	3.78	1.080
	FACA7	.806	4.04	.913
	FACA8	.701	3.89	1.053
	FACA9	.823	4.03	.944
	FACA10	.734	3.97	.925
4. Digital Marketing Strategies Improvement	DMS1	.802	4.06	1.028
	DMS2	.754	4.04	.960
	DMS3	.856	4.08	.955
	DMS4	.765	4.04	.983
	DMS5	.815	4.06	1.013
	DMS6	.808	4.18	.929
	DMS7	.903	4.08	1.068
	DMS8	.811	4.06	.976
	DMS9	.820	4.13	.933
	DMs10	.896	4.16	1.061
5. Improvement in Consumer Attitudes	ICA1	.932	3.94	1.088
	ICA2	.926	4.12	1.102
	ICA3	.790	3.47	.881
	ICA4	.948	3.64	.997
	ICA5	.885	3.69	1.046
	ICA6	.858	3.75	1.004
	ICA7	.901	3.57	.995
	ICA8	.898	3.74	1.092
	ICA9	.954	3.69	1.055
	ICA10	.914	3.52	1.108

Introduction about CFA and EFA

In scale development and scale adaptation investigations, confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) are two often utilized methodologies. It is advised to employ EFA if the relationships between the elements are unknown, however if the relationships are evaluated and the factors are connected elements are understood, and using CFA is advised. EFA is a statistical method used to identify underlying latent variables in the social sciences. In other words, EFA stands out as a scale growth strategy. It is employed in situations when it is unknown how many factors exist between the scale's elements and which factors are influenced by which items. Since in the present study the scale was adapted from earlier studies. Thus, the joint distribution of a set of variables may be investigated and summarized using the statistical approach known as exploratory factor analysis (EFA), which estimates the link between the observed variables and unobserved but theorized factors. It is predicated on the idea that covariance between measured variables results from a smaller group of latent factors that are connected to each observable variable in varied degrees (known as the common factor model assumption).

When there is a solid model assumption, CFA is applied. With CFA, a fresh data set is used to look at the possibility of an already established structure. CFA should be employed in scale development studies to evaluate the reliability of the structure discovered using EFA (Worthington & Whittaker, 2006). All analyses were performed using and SPSS (IBM Corp, 2016) statistical software packages and AMOS. To be specific EFA was performed using SPSS, whereas CFA was performed using AMOS. In the first step, factors were explored and then tested in CFA.

Table 2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.928
Bartlett's Test of Sphericity	Approx. Chi-Square	8475.45
	df	927
	Sig.	.000

Before doing the EFA, the data's adequacy for factor analysis was evaluated using the Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (Dziuban and Shirkey, 1974). Maximum likelihood extraction, un-rotated exploratory factor analysis (EFA), and eigenvalues greater than one were used in the initial study. Further, in order to evaluate the theoretical framework, we also used EFA with promax rotation and enforced five-factor solutions as proposed in the present study. After that, CFA was carried out utilizing maximum likelihood estimate.

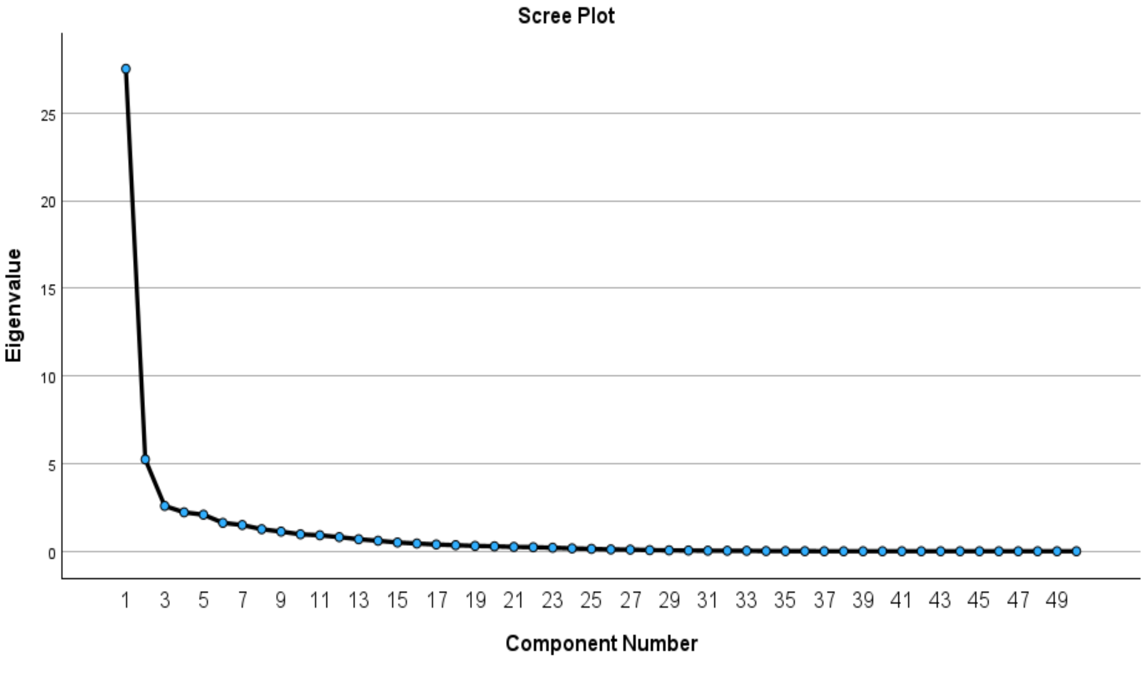

Figure 1 Measurement

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy is a statistic that indicates the suitability of the data for factor analysis. In this case, the KMO value is 0.928, which is considered excellent (values closer to 1 indicate better sampling adequacy). A KMO value greater than 0.6 generally suggests that the data is suitable for factor analysis, and the value of 0.928 strongly supports the appropriateness of performing such an analysis on the given dataset.

The Bartlett's Test of Sphericity tests the null hypothesis that the correlation matrix is an identity matrix, implying that the variables are unrelated and unsuitable for factor analysis. The approximate Chi-Square value of 8475.45 with 927 degrees of freedom and a significant value ($p < 0.001$) indicates that the correlation matrix is not an identity matrix and that significant relationships exist among the variables. Therefore, Bartlett's test confirms that the data is suitable for factor analysis, providing further assurance that factor analysis can be performed to identify underlying patterns in the data.

Table 2 Results

		Initial Eigenvalues[a]			Rotation Sums of Squared Loadings			
	Component	Total	% of Variance	Cumulative %	Total	Total	% of Variance	Cumulative %
Raw	1	27.518	52.103	52.103	27.518	10.310	19.521	19.521
	2	5.240	9.921	62.024	5.240	7.376	13.966	33.487
	3	2.586	4.897	66.921	2.586	6.587	12.472	45.958
	4	2.219	4.202	71.123	2.219	6.302	11.933	57.892
	5	2.086	3.950	75.073	2.086	3.929	7.440	65.331
	6	1.620	3.067	78.140	1.620	3.244	6.142	71.473
	7	1.496	2.833	80.972	1.496	3.237	6.129	77.603
	8	1.258	2.382	83.354	1.258	2.644	5.007	82.610
	9	1.120	2.121	85.476	1.120	1.513	2.866	85.476
	10	.967	1.830	87.306				
	11	.911	1.725	89.030				
	12	.807	1.528	90.558				
	13	.686	1.298	91.856				
	14	.599	1.134	92.990				
	15	.499	.945	93.935				
	16	.442	.836	94.771				
	17	.385	.729	95.500				
	18	.346	.656	96.156				
	19	.305	.577	96.733				
	20	.281	.533	97.266				
	21	.248	.469	97.735				
	22	.229	.434	98.169				
	23	.201	.381	98.550				
	24	.164	.310	98.860				
	25	.136	.257	99.118				
	26	.104	.197	99.314				
	27	.092	.175	99.489				
	28	.064	.121	99.610				
	29	.053	.100	99.710				
	30	.042	.080	99.790				
	31	.031	.059	99.849				
	32	.028	.053	99.902				
	33	.026	.048	99.951				
	34	.012	.024	99.974				
	35	.008	.016	99.990				
	36	.005	.010	100.000				
	37	.131	.297	97.041				
	38	.120	.273	97.314				
	39	.116	.263	97.577				
	40	.113	.257	97.834				
	41	.103	.233	98.067				
	42	.100	.228	98.295				
	43	.090	.204	98.499				
	44	.082	.187	98.686				
	45	.077	.176	98.862				
	46	.073	.166	99.028				
	47	.068	.154	99.182				
	48	.063	.143	99.325				
	49	.058	.131	99.456				
	50	.048	.109	99.565				

The Eigenvalues and variance analysis from the principal component analysis (PCA) show that the first few components explain a significant portion of the total variance in the data. The first component alone accounts for 52.103% of the variance, followed by the second component at 9.921%, and the third at 4.897%, bringing the cumulative explained variance to 66.921% after three components. By the time we reach the sixth component, the explained variance rises to 78.140%, and the cumulative variance reaches 85.476% with the inclusion of the ninth component. Components beyond this point contribute less to the total variance, indicating that a smaller number of components are sufficient to represent the majority of the information in the dataset. This suggests that dimensionality reduction could be applied to retain the essential information while simplifying the dataset.

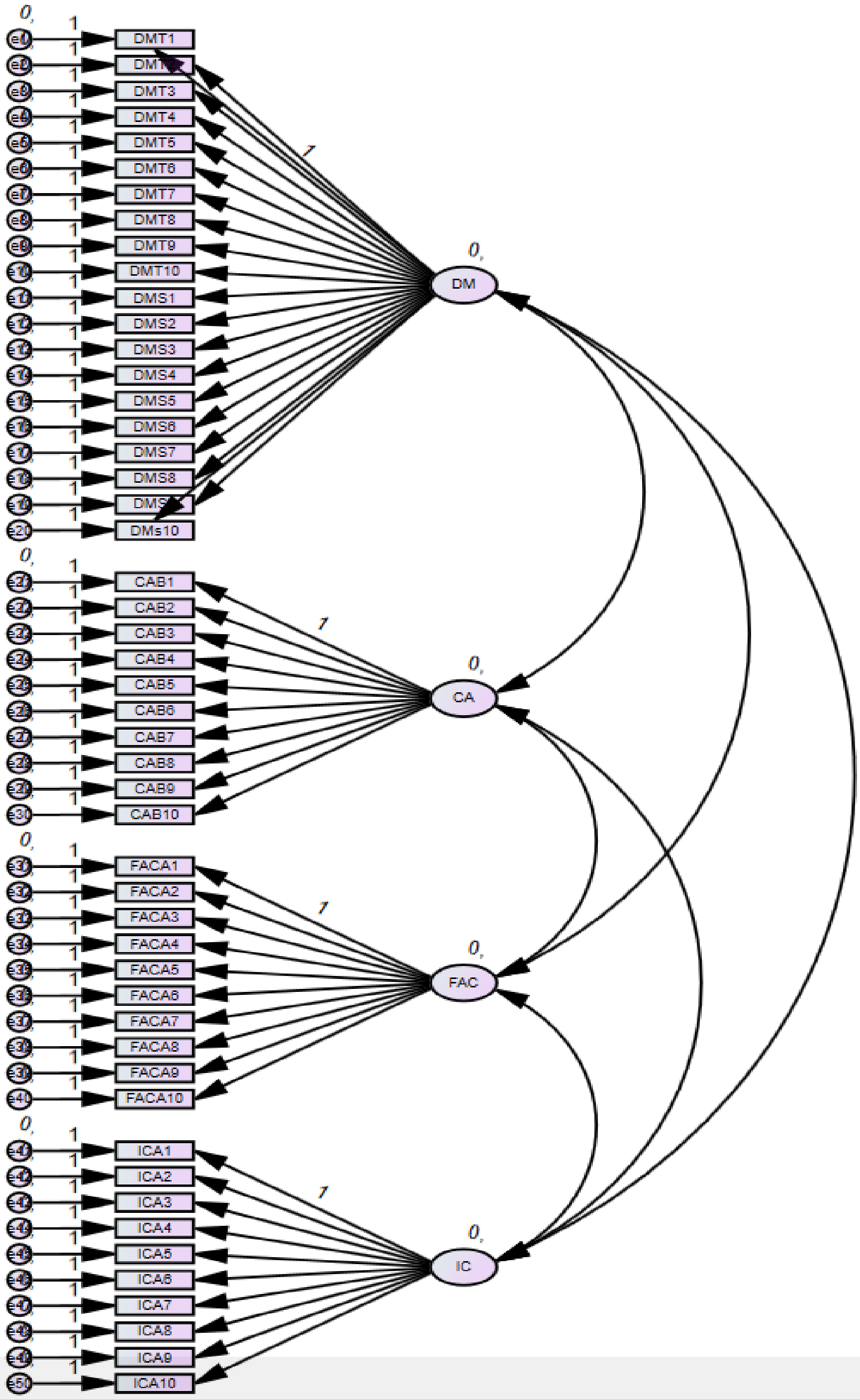

Figure 2 CFA output

Confirmation Factor Analysis

The model was initially given with five latent components as mentioned in the literature and further found five factors in EFA as well. Given that the items had appropriate skewness and kurtosis, standardised coefficients and a maximum likelihood estimation model were applied. Based on the theoretical founding and result of EFA, we performed CFA with five constructs (See figure 2). First, chi-square, CFI, RMSEA, and SRMR values were used to analyze the models. The number of data with high model fit indices was displayed in the table. The below mentioned table exhibits that the calculated values of model fit indicators are more than the suggestion parameters, thus CFA model said to show a good model-data fit. Structural Equation Modeling (SEM) was used in confirmatory factor analysis to ascertain the stability and reliability of the five-component structure of OCB. We started with the OCB's five-component a priori framework. The values of the four OCB factors were calculated using AMOS, and they were permitted to co-vary with one another. (See figure below). The data initially showed a good match to the proposed measurement model, according to fit indices. In a stand-alone evaluation of the model fit for the purpose of construct validity evaluation, Sun (2005) recommends using Standardized Root Mean Square Residual (SRMR), Tucker-Lewis Index (TLI), which is the same as Non-normed Fit Index (NNFI), McDonald's Centrality Index (Mc), Root Mean Square Error of

Approximation (RMSEA), and Comparative Fit Index (CFI), among the many fit indices that are currently available. Table 3 presents the outcomes of CFA using AMOS. The results of the CFA's model fit indices are shown in Table 4, and they show that the measurement model exhibits a respectably excellent model fit.

Table 4: Model fit Indicators

Index	**Model values**	**Suggested Parameters**
Chi square/df	2.72	<3 (Kline, 1998)
Goodness of Fit index	8.01	>=0.90 (Hair et al., 2017)
Comparative Fit index	8.22	>=0.90 Hu and Bentler (1999)
Incremental Fit index	9.32	>=0.90 Hair et al (2017)
Root Mean square error of approximation (RMSEA)	0.046	<=.05 (Byrne, 1998)
Root Mean square residual (SRMR)	0.042	<=.05 (Hu and Bentler, 1999)

The model fit indicators provided in Table 4 assess the goodness of fit of the model and its alignment with the data. The Chi square/df ratio is 2.72, which is well below the recommended threshold of 3 (Kline, 1998), indicating a good fit. The Goodness of Fit Index (GFI) value of 8.01 is higher than the recommended 0.90 (Hair et al., 2017), suggesting a strong fit. Similarly, the Comparative Fit Index (CFI) value of 8.22 exceeds the 0.90 benchmark (Hu & Bentler, 1999), further supporting the model's validity. The Incremental Fit Index (IFI) is 9.32, also above the 0.90 threshold (Hair et al., 2017), showing that the model performs well when compared to other models. The Root Mean Square Error of Approximation (RMSEA) is 0.046, well below the 0.05 cutoff (Byrne, 1998), indicating a close fit between the model and the data. Finally, the Standardized Root Mean Square Residual (SRMR) is 0.042, which is also below the recommended 0.05 (Hu & Bentler, 1999), confirming that the residuals are small and the model fits the data well. All fit indices suggest that the model provides a good fit and is appropriate for explaining the relationships in the data.

Conclusion

This study provides empirical validation of the relationship between digital marketing and consumer attitudes through Confirmatory Factor Analysis (CFA), confirming the structural integrity of key constructs such as brand trust, perceived value, engagement, and purchase intention. The findings highlight that digital marketing strategies significantly shape consumer perceptions and decision-making, with engagement and trust emerging as critical mediators in influencing purchase intent. The CFA results demonstrate a strong model fit, reinforcing the importance of these factors in the consumer-brand interaction process. this research ensures that the identified constructs accurately represent consumer responses to digital marketing initiatives. The study's outcomes emphasize the necessity for businesses to optimize their digital marketing strategies by fostering greater consumer engagement, building trust, and enhancing perceived value. These insights offer actionable recommendations for marketers to refine content personalization, improve customer interactions, and strengthen brand positioning in a highly competitive digital marketplace. Furthermore, the validated factor structure serves as a theoretical foundation for future research exploring the evolving dynamics of digital consumer behavior. The study also underscores the increasing importance of leveraging data-driven insights and advanced analytical methods to adapt to shifting consumer expectations. As digital marketing continues to evolve, companies must remain agile and innovative, ensuring that their marketing efforts effectively resonate with consumer preferences and behavioral patterns. By integrating these empirical findings into strategic decision-making, businesses can enhance brand loyalty, optimize digital engagement, and drive sustainable growth in the digital economy.

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