

Influence of Digital Marketing on Rural Consumer Buying Behaviour in Tamil Nadu

Mr.S.Sundaravadivelu*

Research Scholar

Dr.D.Muruganandam**

Professor and Head

^{1,2}Department of Management, Bharathiar University Post Graduate Extension and Research centre, Erode, Tamil Nadu, India

Abstract : This study explores the factors influencing consumer behavior towards digital marketing and online shopping in rural areas, specifically in Erode and Namakkal Districts. Utilizing exploratory factor analysis (EFA) on data gathered from 280 respondents through a convenience sampling technique, the research identifies key dimensions affecting online shopping behavior. The findings reveal four primary factors: Digital Marketing Influence and Purchase Decisions, Trust and Shopping Preferences, Accessibility and Digital Engagement, and Social Influence and Urban-Rural Divide. The study shows that promotional offers, online reviews, and awareness play a significant role in consumer decision-making. Trust concerns, such as fraud fears and payment preferences, along with infrastructure limitations like slow internet, also impact purchasing decisions. Additionally, digital marketing's effectiveness is influenced by internet accessibility, regional language ads, and digital literacy. Social factors, including word-of-mouth and geographical disparities, further shape consumer behavior. Based on these insights, the research suggests that businesses focus on enhancing trust through secure transactions, promote localized content, and address infrastructure challenges to increase consumer engagement. Leveraging influencer marketing and offering omnichannel shopping experiences can further boost online sales. This study provides valuable insights for businesses targeting rural consumers, helping them craft more effective, consumer-focused digital marketing strategies that cater to the unique preferences and challenges of rural markets.

Keywords: Digital Marketing, Digital Engagement, Social Influence and Urban-Rural Divide

Introduction

The emergence of digital marketing has revolutionized the way organizations interact with consumers, offering novel opportunities for engagement, reach, and influence. In the context of rural Tamil Nadu, the impact of digital marketing is particularly pronounced, as it has enabled companies to penetrate previously untapped markets and cater to the distinctive needs of rural consumers. The rural regions of Tamil Nadu represent a vast market with a diverse population, characterized by varied socioeconomic backgrounds, cultural traditions, and purchasing behaviors. The increasing penetration of the internet, smartphones, and digital payment systems in these areas has paved the way for the rapid adoption of online platforms. This transformation has empowered rural consumers with access to information, enhanced product choices, and competitive pricing, which were previously limited in traditional marketplaces.

Digital marketing strategies, such as social media campaigns, search engine optimization, influencer marketing, and localized content, play a pivotal role in shaping the buying behavior of rural consumers. Factors like affordability, brand trust, and cultural relevance often influence purchasing decisions in these areas. As digital platforms continue to gain popularity, businesses must understand and adapt to the unique preferences and challenges faced by rural consumers. This study explores the evolving landscape of digital marketing in rural Tamil Nadu and its impact on consumer buying behavior. It aims to examine how digital platforms influence awareness, decision-making, and the purchasing process among rural consumers. The findings of this study will provide valuable insights for businesses seeking to optimize their digital marketing strategies to effectively cater to the rural market in Tamil Nadu.

Literature Review

The Indian rural market has been a significant focus of attention for marketers and researchers alike, given its immense potential and unique characteristics (Hakhroo, 2020). The rural consumer, with their distinct preferences and behaviour patterns, have presented both challenges and opportunities for businesses looking to expand their reach. (Hakhroo, 2020) This study aims to explore the impact of digital marketing strategies on the buying behaviour of rural consumers in Tamil Nadu, a state known for its diverse cultural landscape and rapidly evolving consumer dynamics. The growth of digital technologies and the increasing penetration of internet and smartphone usage in rural areas have significantly transformed the way consumers engage with brands and make purchasing decisions. (Parida&Sahney, 2017) While the existing literature provides valuable insights into the general characteristics of rural markets, there is a need to delve deeper into the specific impact of digital marketing on the buying behaviour of rural consumers in the context of Tamil Nadu.

Researchers have highlighted the immense potential of the rural market in India, noting its vast consumer base and the unique nuances that differentiate it from urban markets (Nayak, 2021). The study by Renuka Devi and Swathi explores the challenges faced by digital marketers in rural areas, identifying issues such as poor internet connectivity, high costs of digital platforms, and low digital literacy as key barriers to effective digital marketing campaigns. (Nayak, 2021) In contrast, the study by Joy Suganya emphasizes the advantages of digital marketing in rural areas, including its time-efficiency, significant reach, and accessibility. (Nayak, 2021) The paper by Suganya further suggests that the rural market is more product-driven than service-driven, and having product knowledge available to customers ahead of time can aid in forecasting consumer behaviour and preparing for market outcomes. (Yasmin et al., 2015)

(Ravi & Rajasekaran, 2023) Another study by Sunder and Subramaniam delves into the factors influencing rural consumer behaviour, highlighting the role of socio-economic status, cultural norms, and product awareness in shaping purchasing decisions. The paper by Vamshidhar and Goud examines the evolving consumer preferences and market potential in rural areas, noting the growing similarities between rural and urban consumption patterns. (NADKARNI, 2022). The study by Obi et al. provides empirical evidence on the role of digital marketing in enhancing rural agricultural transformation in Nigeria, highlighting the potential for digital technologies to drive economic development in rural areas. (Ogbeide-Osaretin & Ebhote, 2020)

The rural market in India is characterized by a vast and diverse consumer base, with a significant portion of the country's middle-class and disposable income (Kumar, 2013). Understanding the unique needs and preferences of rural consumers is crucial for the success of any marketing strategy, as they often differ from their urban counterparts. Researchers have highlighted the importance of understanding the growing complexities of the rural market and the need to develop appropriate marketing mix strategies to cater to the rural consumer (Kumar, 2013). In the digital age, the role of digital marketing in reaching and engaging with rural consumers has become increasingly significant. Digital marketing offers a cost-effective and efficient way for businesses to connect with rural consumers, enabling them to access a wider range of products and services. (Nayak, 2021) (Parida & Sahney, 2018) However, the adoption and impact of digital marketing in rural areas is still an unexplored field, with limited research on the specific challenges and opportunities it presents.

Moreover, studies have explored the influence of cultural factors on the brand loyalty of Indian rural consumers, suggesting that marketers need to consider the role of cultural nuances in their approach to this segment. (Parida & Sahney, 2017) As the rural market continues to evolve, it is essential to explore the impact of emerging digital marketing trends on the buying behaviour of rural consumers.

Research Gap

Existing studies have also explored the potential of digital marketing in reaching and engaging with rural consumers. The cost-effective and efficient nature of digital marketing platforms, such as social media, e-commerce, and mobile applications, have opened up new avenues for businesses to connect with rural consumers. However, the challenges faced by digital marketers in rural areas, such as limited internet connectivity, low digital literacy, and language barriers, have also been highlighted in the literature. The existing literature on rural marketing in India has primarily focused on the traditional aspects of the rural market, such as distribution channels, pricing strategies, and promotional activities. However, there is a need to investigate the specific impact of digital marketing on the purchasing decisions of rural consumers, particularly in the context of Tamil Nadu.

Methodology

The researchers employed exploratory factor analysis to uncover the underlying dimensions influencing consumer behavior towards digital marketing and online shopping. The data was collected through a survey administered to a sample of consumers from Erode and Namakkal Districts, utilizing a Convenient Sampling Techniques. A total of 280 respondents were selected from villages within each district. By focusing on online consumers, this study provides targeted insights into how digital marketing influences buying behavior in rural areas, offering valuable data for understanding consumer trends and preferences in these regions. The survey instrument assessed 20 variables related to respondents' perceptions and experiences of digital marketing and online shopping. Participants responded using a 7-point Likert scale, with options ranging from "Strongly Disagree" to "Strongly Agree". The researchers conducted factor analysis with Varimax rotation using IBM SPSS Statistics software to analyze the survey data and identify the key underlying dimensions.

Data Analysis

Reliability analysis is a fundamental component of research methodology, as it enables researchers to assess the consistency and stability of their measurement instruments. One commonly used metric for evaluating internal consistency is Cronbach's alpha, which provides an estimate of the proportion of measurement variance attributable to the true score of the underlying construct. (Forero, 2014)

Cronbach's alpha is conceptually analogous to split-halves reliability, where two parts of the same test are correlated to estimate the reliability of the full test. (Forero, 2014) This metric assumes that all items in a test or scale are equivalent, and it corresponds to the reliability of the full test computed by extending the properties of one unit multiple times. (Forero, 2014)

A high Cronbach's alpha value, typically above 0.7, indicates that the items in a scale are closely related and likely measure the same underlying construct. (Forero, 2014)

(Sullivan, 2011) Conversely, a low alpha value may suggest the scale needs refinement or that the items do not adequately capture the intended variable.

Table 1.0 Reliability and Scale Statistics

| Cronbach's alpha | Cronbach's alpha based on Standardized items | No of Items | Mean | Variance | Std. Deviation |
|------------------|--|-------------|---------|----------|----------------|
| 0.946 | 0.939 | 20 | 70.2136 | 214.735 | 14.65384 |

The Cronbach's alpha coefficient of 0.946 suggests a high degree of internal consistency among the 20 scale items, indicating that the items are strongly correlated and effectively measure the same underlying construct. The slightly lower Cronbach's alpha based on standardized items implies that standardizing the items does not substantially impact the scale's reliability. The dataset exhibits a mean score of 70.2136, a variance of 214.735, and a standard deviation of 14.65384, reflecting a moderate dispersion of scores around the mean. Overall, the high Cronbach's alpha value confirms the scale's high reliability in measuring the intended concept, rendering it suitable for further analysis or research purposes.

Factor analysis is a powerful multivariate statistical technique employed to identify and examine the underlying structures or latent variables within a set of observed variables. Its primary objective is to simplify and summarize the complex relationships among a large number of interrelated variables by reducing them to a smaller set of representative factors or dimensions (Cattell, 1965). This analytical approach is extensively utilized in various fields, including psychology, sociology, marketing, and finance, to uncover the factors that contribute to the observed patterns in the data. The fundamental premise of factor analysis is that a smaller number of unobserved latent variables, or factors, account for the relationships among the observed variables (Schwartz, 1971). The implementation of factor analysis involves several key steps. Initially, the suitability of the data for factor analysis is assessed by examining the correlation matrix, the Kaiser-Meyer-Olkin measure of sampling adequacy, and Bartlett's test of sphericity to ensure the dataset is appropriate for this analytical technique. Subsequently, factors are extracted using methods such as principal component analysis, principal axis factoring, or maximum likelihood factoring (Deku et al., 2024). The determination of the appropriate number of factors to retain is based on criteria like the eigenvalue-greater-than-one rule, the scree plot, and the percentage of variance explained. Factor analysis can be categorized into two main types: exploratory factor analysis and confirmatory factor analysis. EFA is employed when researchers have limited prior

knowledge about the underlying factor structure, allowing them to explore and uncover patterns within the data. In contrast, CFA is applied when researchers aim to test specific hypotheses about the factor structure. Through these analytical processes, factor analysis helps to unveil hidden patterns, reduce the complexity of the data, and enhance the interpretability of research findings (Matsunaga, 2010).

Table 2

Influence of Digital Marketing in rural consumer behavior

| Item Statistics | Mean | Std. Deviation |
|--|--------|----------------|
| I often see digital ads on social media, websites, or apps. | 3.5773 | 1.17370 |
| Digital marketing helps me learn about new products. | 3.1364 | 1.22364 |
| I have seen digital ads in my regional language. | 3.3727 | 1.03685 |
| Digital ads provide better product details than TV or newspapers. | 3.4727 | 1.04431 |
| I trust online ads when making purchases. | 3.7636 | 1.05057 |
| I have easy access to the internet and digital devices. | 3.4045 | 1.15271 |
| Internet data costs affect my access to digital ads. | 2.9909 | 1.15070 |
| Slow internet affects my online shopping experience. | 3.2545 | 1.11802 |
| I have bought a product after seeing a digital ad. | 3.4409 | 1.02532 |
| Online reviews influence my buying decisions. | 3.6182 | 1.08524 |
| Discounts in digital ads encourage me to buy online. | 3.7727 | 1.02622 |
| I compare prices online before buying in local stores. | 3.6318 | 1.12906 |
| I worry about fraud when shopping online. | 3.5045 | 1.17624 |
| I prefer cash-on-delivery over online payments. | 3.5000 | 1.01361 |
| Some online ads are misleading. | 3.5227 | .99974 |
| My family and community influence my online shopping. | 3.8227 | .95584 |
| I prefer buying from local markets over online stores. | 3.5500 | 1.01687 |
| Digital marketing is more useful for urban buyers than rural ones. | 3.7545 | .92836 |
| Word-of-mouth influences my online shopping. | 3.2500 | 1.21115 |
| Rural consumers need more awareness about online shopping. | 3.8727 | .95189 |

The influence of digital marketing in rural consumer reveals valuable insights into consumer perceptions of digital marketing and online shopping behavior. The statement "Rural consumers need more awareness about online shopping" has the highest mean (3.8727) with a relatively low standard deviation (0.95189), indicating strong consensus among respondents with minimal variation. Similarly, "My family and community influence my online shopping" (Mean = 3.8227, SD = 0.95584) and

"Discounts in digital ads encourage me to buy online" (Mean = 3.7727, SD = 1.02622) suggest that social and financial incentives play a significant role in online purchasing decisions.

Trust in digital ads is reflected in the mean score of 3.7636 (SD = 1.05057), showing that while many respondents consider online advertisements reliable, there is some variability in this perception. Additionally, "Digital marketing is more useful for urban buyers than rural ones" (Mean = 3.7545, SD = 0.92836) implies a perceived urban-rural digital divide. Price sensitivity is evident as many respondents compare online prices before purchasing in local stores (Mean = 3.6318, SD = 1.12906). Concerns about online shopping security and fraud remain significant, as seen in "I worry about fraud when shopping online" (Mean = 3.5045, SD = 1.17624) and "Some online ads are misleading" (Mean = 3.5227, SD = 0.99974). Interestingly, "I prefer buying from local markets over online stores" (Mean = 3.5500, SD = 1.01687) suggests a strong preference for offline shopping despite the growing influence of digital ads.

Table 3.0
KMO AND BARTLETT'S TEST

| KMO and Bartlett's Test | | |
|--|--------------------|----------|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .874 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 3125.418 |
| | df | 190 |
| | Sig. | .000 |

The results of the KMO and Bartlett's Test demonstrate that the dataset is suitable for Factor Analysis. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy, with a value of 0.874, significantly exceeds the recommended threshold of 0.6, indicating that the sample size is adequate for factor extraction. This high KMO value suggests that the variables share common variance and are appropriate for conducting factor analysis. Furthermore, the Bartlett's Test of Sphericity has a Chi-Square value of 3125.418 with 190 degrees of freedom and a significance value of 0.000. Since the p-value is less than 0.05, this confirms that the correlation matrix is not an identity matrix, meaning that there are significant relationships among the variables. This justifies the application of factor analysis to the dataset.

Table 4.0
Communalities

| Factors | Initial | Extraction |
|--|----------------|-------------------|
| I often see digital ads on social media, websites, or apps. | 1.000 | .595 |
| Digital marketing helps me learn about new products. | 1.000 | .675 |
| I have seen digital ads in my regional language. | 1.000 | .734 |
| Digital ads provide better product details than TV or newspapers. | 1.000 | .632 |
| I trust online ads when making purchases. | 1.000 | .625 |
| I have easy access to the internet and digital devices. | 1.000 | .598 |
| Internet data costs affect my access to digital ads. | 1.000 | .720 |
| Slow internet affects my online shopping experience. | 1.000 | .797 |
| I have bought a product after seeing a digital ad. | 1.000 | .658 |
| Online reviews influence my buying decisions. | 1.000 | .707 |
| Discounts in digital ads encourage me to buy online. | 1.000 | .762 |
| I compare prices online before buying in local stores. | 1.000 | .469 |
| I worry about fraud when shopping online. | 1.000 | .796 |
| I prefer cash-on-delivery over online payments. | 1.000 | .707 |
| Some online ads are misleading. | 1.000 | .676 |
| My family and community influence my online shopping. | 1.000 | .650 |
| I prefer buying from local markets over online stores. | 1.000 | .623 |
| Digital marketing is more useful for urban buyers than rural ones. | 1.000 | .753 |
| Word-of-mouth influences my online shopping. | 1.000 | .847 |
| Rural consumers need more awareness about online shopping. | 1.000 | .648 |
| Extraction Method: Principal Component Analysis. | | |

The above table shows that the extent to which each variable contributes to the extracted factors in the Principal Component Analysis. The "Initial" column contains values set to 1.000 for all variables, as PCA assumes that each variable initially holds all its variance. The "Extraction" column represents the proportion of variance for each item that is explained by the extracted factors. A higher extraction value indicates that the variable strongly contributes to the underlying factors, while lower values suggest weaker contributions.

Among the items, "Word-of-mouth influences my online shopping" has the highest communality score (0.847), indicating a strong association with the identified factors. Similarly, "Slow internet affects my online shopping experience" and "I worry about fraud when shopping online" show high communalities, suggesting that these concerns significantly influence consumer behavior. Other variables with strong contributions include "Discounts in digital ads encourage me to buy online" and "Digital marketing is more useful for urban buyers than rural ones", implying that promotional offers and geographical differences are important determinants in digital marketing.

In contrast, "I compare prices online before buying in local stores" has the lowest communality score (0.469), suggesting a weaker connection to the extracted factors. However, it still maintains a moderate level of explanation within the factor structure.

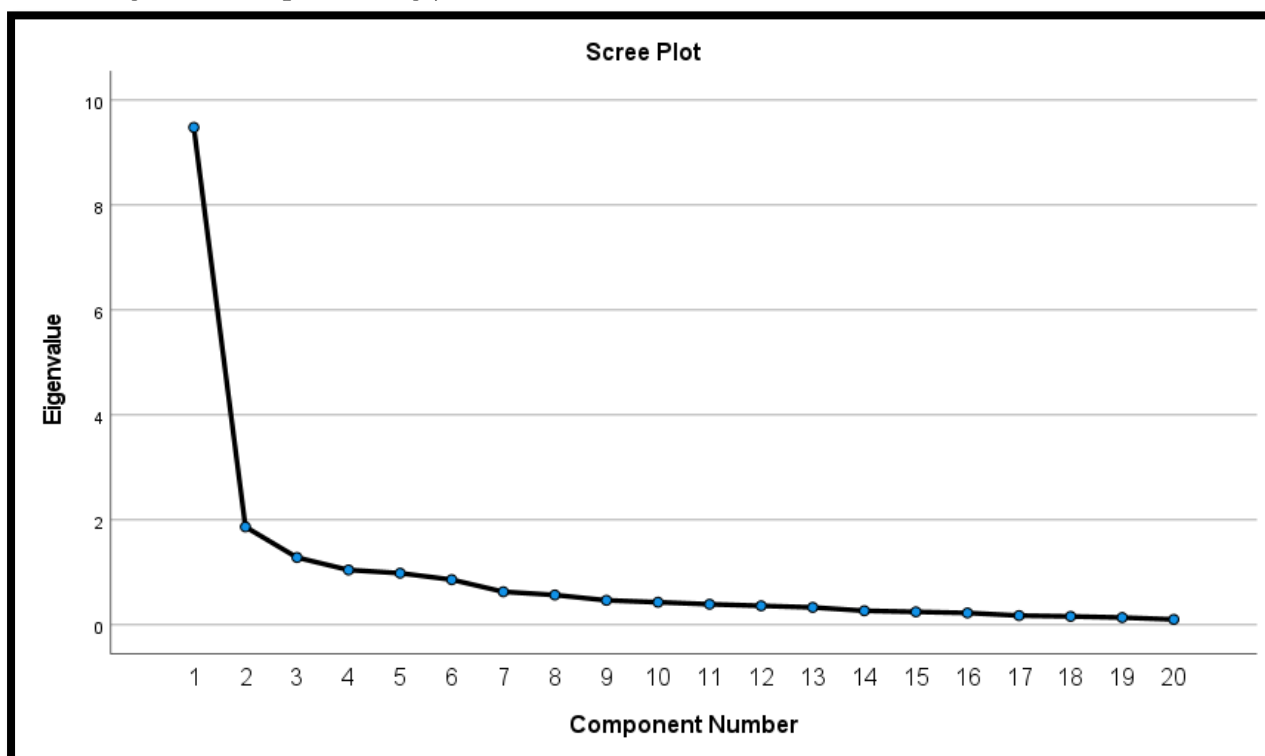
Table 5.0
Total Variance Explained

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|-----------|---------------------|---------------|--------------|-------------------------------------|---------------|--------------|-----------------------------------|---------------|--------------|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 9.481 | 47.404 | 47.404 | 9.481 | 47.404 | 47.404 | 4.101 | 20.505 | 20.505 |
| 2 | 1.866 | 9.329 | 56.733 | 1.866 | 9.329 | 56.733 | 3.601 | 18.007 | 38.512 |
| 3 | 1.282 | 6.410 | 63.143 | 1.282 | 6.410 | 63.143 | 3.547 | 17.737 | 56.248 |
| 4 | 1.044 | 5.221 | 68.364 | 1.044 | 5.221 | 68.364 | 2.423 | 12.116 | 68.364 |
| 5 | .983 | 4.915 | 73.279 | | | | | | |
| 6 | .860 | 4.298 | 77.577 | | | | | | |
| 7 | .629 | 3.143 | 80.720 | | | | | | |
| 8 | .567 | 2.837 | 83.557 | | | | | | |
| 9 | .466 | 2.329 | 85.886 | | | | | | |
| 10 | .429 | 2.146 | 88.032 | | | | | | |
| 11 | .391 | 1.955 | 89.987 | | | | | | |
| 12 | .361 | 1.804 | 91.792 | | | | | | |
| 13 | .331 | 1.656 | 93.447 | | | | | | |
| 14 | .267 | 1.334 | 94.781 | | | | | | |
| 15 | .246 | 1.229 | 96.010 | | | | | | |
| 16 | .225 | 1.124 | 97.134 | | | | | | |
| 17 | .175 | .875 | 98.009 | | | | | | |

| | | | | | | | | | |
|----|------|------|---------|--|--|--|--|--|--|
| 18 | .159 | .796 | 98.805 | | | | | | |
| 19 | .137 | .686 | 99.491 | | | | | | |
| 20 | .102 | .509 | 100.000 | | | | | | |

Extraction Method: Principal Component Analysis.

The Total Variance Explained table provides a summary of the variance accounted for by each component during the Principal Component Analysis. The Initial Eigenvalues show that the first component explains 47.404% of the total variance, making it the most significant factor in explaining the data structure. The second component explains 9.329%, and the third explains 6.410%. Together, the first three components account for 63.143% of the variance, indicating that a significant portion of the data's variability can be explained by just these three factors.



The total variance explained by the first four components reaches 68.364%, which is quite substantial, suggesting that the remaining components contribute less to explaining the variance. The Extraction Sums of Squared Loadings correspond to the amount of variance explained by the factors retained after the extraction process. The first four factors remain the most influential, with the cumulative variance after the first four components totaling 68.364%. This implies that the analysis focuses on these four factors for further interpretation, while additional components contribute less significantly.

After rotation, the first four components remain highly significant. The first factor still explains 20.505% of the variance, the second explains 18.007%, and the third explains 17.737%, with the fourth explaining 12.116%. The cumulative variance after rotation for the first four factors is 56.248%. Rotation ensures that the factors are more

interpretable by maximizing the variance explained by each factor while keeping the components as uncorrelated as possible. The cumulative variance for the first four rotated components is 56.248%, indicating that these four factors sufficiently explain a majority of the data's variability.

Table 6.o
Rotated Component Matrix

| Rotated Component Matrix ^a | Component | | | |
|--|-----------|------|------|------|
| | 1 | 2 | 3 | 4 |
| Discounts in digital ads encourage me to buy online. | .785 | | | |
| Online reviews influence my buying decisions. | .736 | | | |
| Rural consumers need more awareness about online shopping. | .716 | | | |
| I trust online ads when making purchases. | .654 | | | |
| I often see digital ads on social media, websites, or apps. | .619 | | | |
| My family and community influence my online shopping. | .580 | | | |
| I worry about fraud when shopping online. | | .799 | | |
| I prefer cash-on-delivery over online payments. | | .765 | | |
| Slow internet affects my online shopping experience. | | .682 | | |
| I prefer buying from local markets over online stores. | | .630 | | |
| Some online ads are misleading. | | .518 | | |
| I compare prices online before buying in local stores. | | .518 | | |
| Digital marketing helps me learn about new products. | | | .790 | |
| Internet data costs affect my access to digital ads. | | | .781 | |
| I have seen digital ads in my regional language. | | | .763 | |
| Digital ads provide better product details than TV or newspapers. | | | .708 | |
| I have easy access to the internet and digital devices. | | | .592 | |
| Word-of-mouth influences my online shopping. | | | | .871 |
| I have bought a product after seeing a digital ad. | | | | .609 |
| Digital marketing is more useful for urban buyers than rural ones. | | | | .568 |

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.^a

a. Rotation converged in 7 iterations.

The Rotated Component Matrix presents the factor loadings of each variable after applying Principal Component Analysis (PCA) with Varimax Rotation. The table groups the variables into four distinct components, each representing an underlying factor that explains patterns in consumer behavior toward digital marketing and online shopping.

Digital Marketing Influence and Purchase Decisions:The highest loading variables under this factor include "Discounts in digital ads encourage me to buy online" (0.785), "Online reviews influence my buying decisions" (0.736), and "Rural consumers need more awareness about online shopping" (0.716).This suggests that promotional offers, reviews, and awareness significantly influence consumer behavior in online shopping.

Trust and Shopping Preferences:Key variables in this factor include "I worry about fraud when shopping online" (0.799), "I prefer cash-on-delivery over online payments" (0.765), and "Slow internet affects my online shopping experience" (0.682).This indicates that trust, security concerns, and infrastructure issues (like internet speed) impact consumers' purchasing decisions.

Accessibility and Digital Engagement:High-loading variables include "Digital marketing helps me learn about new products" (0.790), "Internet data costs affect my access to digital ads" (0.781), and "I have seen digital ads in my regional language" (0.763).This factor reflects how digital literacy, internet access, and regional language support affect consumer engagement with digital marketing.

Social Influence and Urban-Rural Divide:The strongest loadings under this factor include "Word-of-mouth influences my online shopping" (0.871), "I have bought a product after seeing a digital ad" (0.609), and "Digital marketing is more useful for urban buyers than rural ones" (0.568).This suggests that social recommendations, digital ad exposure, and geographical differences play a significant role in shaping online shopping behavior.

Table 7.0

| Component Transformation Matrix | | | | |
|---|-------|-------|------|-------|
| Component | 1 | 2 | 3 | 4 |
| Digital Marketing Influence and Purchase Decisions | .583 | .539 | .474 | .382 |
| Trust and Shopping Preferences | -.246 | -.215 | .861 | -.390 |
| Accessibility and Digital Engagement | -.769 | .548 | .063 | .323 |
| Social Influence and Urban-Rural Divide | -.090 | -.603 | .174 | .773 |
| Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. | | | | |

The Component Transformation Matrix illustrates how the extracted factors were adjusted through Varimax Rotation to enhance interpretability. The first component, Digital Marketing Influence and Purchase Decisions, retains moderate loadings across all factors, suggesting its broad impact. The second component, Trust and Shopping

Preferences, shows a strong correlation with its rotated structure (0.861), indicating a well-defined factor. The third component, Accessibility and Digital Engagement, initially had a strong negative loading but was redistributed to better align with other variables. The fourth component, Social Influence and Urban-Rural Divide, maintains a high correlation (0.773) within its rotated form, ensuring that social and geographical influences remain distinct. Overall, the transformation confirms that rotation has successfully clarified the factor structure, making each dimension more interpretable and distinct in explaining consumer behavior toward digital marketing.

Results and Discussions

To improve the effectiveness of digital marketing and enhance consumer engagement, businesses should focus on building trust by ensuring transparency in online transactions, promoting verified reviews, and providing secure payment options. Since many consumers are influenced by regional language ads, companies should develop localized and personalized digital marketing strategies to better connect with their target audience. Enhancing internet accessibility, especially in rural areas, is crucial, as slow speeds and high data costs impact digital engagement. Businesses should consider lightweight mobile apps and mobile-friendly content to accommodate users with connectivity issues.

Leveraging discounts and influencer marketing can boost online purchases. Online reviews and word-of-mouth strongly influence buying decisions, so brands should collaborate with influencers and encourage user-generated content to enhance credibility. Many still prefer cash-on-delivery due to trust issues with online payments; e-commerce platforms should continue offering this while promoting secure digital payment methods through incentives. Finally, businesses should bridge online and offline shopping by adopting omnichannel strategies like price-matching and "buy online, pick up in-store" to cater to consumer preferences. Implementing these suggestions can help digital marketers create more effective, consumer-centric strategies that drive engagement and build long-term customer relationships.

Conclusion

This study employed factor analysis to investigate consumer perceptions of digital marketing and online shopping behavior. The analysis identified four key factors influencing consumer engagement: Digital Marketing Influence and Purchase Decisions, Trust and Shopping Preferences, Accessibility and Digital Engagement, and Social Influence and Urban-Rural Divide. The findings suggest that promotional offers, online reviews, and social recommendations significantly impact consumer purchasing decisions, while concerns about fraud, slow internet, and payment security undermine consumer confidence. Moreover, the accessibility of digital ads, particularly in regional languages, enhances consumer engagement, and rural consumers require greater awareness of online shopping opportunities. To maximize the effectiveness of digital

marketing, businesses must adopt trust-building strategies, improve digital infrastructure, localize marketing approaches, and enhance online shopping experiences. A data-driven, consumer-centric approach to digital strategy development can help organizations address both the benefits and challenges associated with online shopping, fostering greater consumer trust, improving engagement, and driving sustainable growth in the digital marketplace.

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