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Article

Differences in the influence of virtual influencers on different consumer groups

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Abstract: This paper uses quantitative research methods to explore the differences in the impact of virtual influencers on different consumer groups in the context of technological integration and innovation. The study uses DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering technology to segment consumers and combines social media behavior analysis with purchase records to collect data to identify differences in consumer behavior under the influence of virtual influencers. Consumers' emotional resonance and brand awareness information about virtual influencers are extracted through sentiment analysis technology. The study finds that there are significant differences in the influence of virtual influencers on different consumer groups, especially in high-potential purchase groups, where the influence of virtual influencers is strong but short-lived. This paper further explores the deep integration of virtual influencer technology with new generation information technologies such as 5G and artificial intelligence, and emphasizes the importance of such technological integration in enhancing the endogenous and empowering capabilities of virtual influencers. The research results show that technological integration and innovation can not only promote the development of virtual influencers, but also provide new technical support for infrastructure construction, especially in the fields of smart cities and industrial production. This paper provides a new theoretical perspective for the market application of virtual influencers and provides practical support for the application of virtual technology in infrastructure construction.

Keywords: virtual influencers; consumer groups; influence differences; brand recognition; purchase intention

1. Introduction

In recent years, the development trend of digital technology and the widespread penetration of social media have jointly spawned virtual influencers, a new group of Internet celebrities, which have rapidly accumulated a huge fan base and opened up a rich commercialization path (Leung et al., 2022; Stein et al., 2024). Virtual influencers have caused a wide and far-reaching impact on young consumer groups with their unique visual image design, highly personalized interaction mode, and efficient content production ability (Peukert et al., 2019; Huang et al., 2020). The differentiated influence of virtual influencers on various consumer groups has not received due academic attention and research (Vrontis et al., 2021; Sands et al., 2022). Most previous studies have focused on the analysis of real influencers or the overall consumer market, and few studies have systematically explored the specific mechanism of virtual influencers in different consumer segments (Thomas and Fowler, 2021; Haenlein et al., 2020). In fact, factors such as consumers' age, gender, interests, hobbies, and cultural background may lead to different acceptance and reaction patterns of virtual influencers. There is still a lack of comprehensive and in-depth discussion on this level of difference analysis (Lu et al., 2022; Kim et al., 2020). Given this, this paper is committed to filling the gap in this research field and aims to carefully analyze the differentiated impact of virtual influencers on various consumer groups. This paper aims to provide a more precise theoretical basis and practical guidance for brand marketing, so as to help brands more effectively utilize virtual influencer resources and achieve accurate positioning and execution of market segmentation strategies (Appel et al., 2020; Cotter, 2019).

Today, research on virtual influencers mainly focuses on their commercial value and fan interaction (Silva et al., 2020; Kang et al., 2020). Studies have shown that the activity of virtual influencers on social platforms and the frequency of interaction with fans directly affect their commercial value (Morrison-Smith and Ruiz, 2020; Mende et al., 2019); some studies have explored how virtual influencers can attract specific groups through customized content and successfully promote brand cooperation (Yung et al., 2021; Han et al., 2022). However, although these studies have provided preliminary insights into the commercial potential of virtual influencers, most studies still focus on the market performance and fan loyalty of virtual influencers, lacking in-depth exploration of the differences among consumer groups (Chopra et al., 2021; Langer et al., 2019). In particular, research on the acceptance, emotional resonance, and consumption behavior of different consumer groups towards virtual influencers is still relatively weak (Bower et al., 2020; Koohang et al., 2023). Therefore, there is a clear research gap in the existing literature when exploring the differences in the interactions between virtual influencers and different consumer groups (El-Said and Aziz, 2022; Leung et al., 2022).

To solve this problem, some studies have begun to try to combine the research framework of consumer behavior and virtual characters and use a combination of qualitative and quantitative methods to explore (Ye et al., 2021; Jin et al., 2019). For example, through questionnaire surveys, the differences in the cognition and purchasing behavior of consumers of different age groups towards virtual influencers are analyzed, and it is found that young groups are more inclined to establish emotional connections with virtual influencers and are easily influenced by them (Liu et al., 2020; Hernandez Urrego, 2019). However, most existing studies remain on the analysis of a single group or a single factor and fail to comprehensively examine the impact of virtual influencers on different consumer groups in multiple dimensions (such as emotional resonance, trust building, brand awareness, etc.) (Al-Emadi and Yahia, 2020; Yarberry and Sims, 2021). In addition, existing studies rarely combine the relationship between the personality characteristics of virtual influencers and the specific behavior patterns of consumer groups (Navarro and Tudge, 2023; Raghuram et al., 2019). Therefore, this paper adopts a multidimensional analysis method, combining qualitative and quantitative research, to comprehensively explore the differences in the impact of virtual influencers on different consumer groups.

This paper is committed to systematically exploring the differences in the impact of virtual influencers on various consumer groups, and then revealing how virtual influencer marketing strategies produce differentiated effects at the consumer behavior level. To achieve this goal, this study divides consumer groups into detailed groups (such as based on age, gender, interests, etc.) and conducts comparative analysis to deeply analyze how factors such as virtual influencers' image shaping, interactive performance, and brand endorsement activities affect the emotional resonance, purchasing decisions, and brand cognition of different groups. This paper examines the specific impact of virtual influencers on each consumer group in different dimensions one by one, revealing their mechanism of action in a diversified market. The study focuses on how the image characteristics of virtual influencers stimulate emotional connections among specific groups, how their interactive performance promotes or hinders consumers' purchasing intentions, and how brand endorsement activities shape or change consumers' cognition and attitudes toward brands. Through this series of rigorous analytical steps, this paper provides solid theoretical support and practical guidance for brands to formulate precise and effective marketing strategies. Ultimately, this study hopes to open up new perspectives for the application of virtual influencers in a diversified consumer market, contribute innovative and practical research results, and help brands stand out in the fierce market competition.

2. Behavioral data collection

2.1. Data sources and collection

This study first sets out to systematically collect consumer behavior data from multiple mainstream social platforms, such as Weibo, Douyin, Instagram, etc. (Poturak and Softic, 2019; Zulfiqar et al., 2019). The focus of data collection covers the following aspects: Various interactive behaviors between consumers and virtual influencers on social platforms, such as likes, comments, shares, and reposts, which can intuitively reflect the consumer's activity level and emotional tendency (Hermes et al., 2020; Miao et al., 2022); consumer purchase history, including purchase frequency, consumption amount, and brand preference information; consumer basic information, such as age, gender, and geographic location, which serves as a key reference dimension for subsequent consumer group segmentation (Nordback and Espinosa, 2019; Beck et al., 2019).

The data collection work mainly relies on social platforms with high activity and rich interactive forms. The specific data collection methods are described as follows:

First, the API interfaces provided by various social platforms are used to realize automatic data capture. These interfaces provide a wide range of data content, including but not limited to specific interaction details such as consumers' likes, comments, shares, and reposts, as well as the text content of comments, which is convenient for emotional tendency analysis. In addition, these data also include fan growth data, which can reflect the changing trend of consumers' attention to virtual influencer-related content; Secondly, when encountering API usage restrictions, a customized web crawler program is deployed to precisely identify and collect data elements such as comments and reposts on the page, so as to fully obtain posts related to virtual influencers and their consumer interaction history; Finally, through cooperation with e-commerce platforms, consumers' purchasing behavior data is obtained. These data record in detail the details of the goods purchased by consumers, the amount of consumption, and whether the purchasing behavior is affected by the promotion activities of virtual influencers, such as whether they participate in promotional activities exclusive to virtual influencers. In addition to Weibo, Tik Tok and Instagram, expand the scope of data collection to include other platforms such as

WeChat and Facebook, which may have more older users, especially WeChat users in China and Facebook users in the West. This will help balance the data representation of young and old groups. In the analysis process, weight the data of different age groups. For example, the participation of young groups is higher, but the feedback from older groups can also be reflected in a weighted manner to ensure the balance of different groups in the analysis. For older consumer groups, conduct supplementary research through other channels (traditional media or telephone surveys, etc.) to obtain these groups' reactions and preferences to virtual influencer endorsements, thereby making up for the lack of platform data. All data are recorded in detail in **Tables 1** and **2**, providing a solid data foundation for subsequent analysis.

Table 1. Social media behavior data.

Consumer ID	Platform Type	Interaction Type	Likes Count	Comments Count	Shares Count	Retweets Count	Sentiment Analysis Result
1	Weibo	Like	50	10	5	2	Positive
2	Douyin	Comment	30	15	3	1	Neutral
3	Instagram	Share	20	5	10	3	Positive
4	Weibo	Retweet	70	12	8	4	Positive
5	Douyin	Like	80	25	12	6	Positive
6	Instagram	Comment	40	18	7	5	Neutral
7	Weibo	Share	15	8	3	2	Negative

Table 1 records the specific behavioral data of consumers interacting with virtual influencers on social platforms (such as Weibo, Douyin, and Instagram).

Table 2. Purchase behavior data.

Consumer ID	Purchased Product	Purchase Amount	Brand Chosen	Influenced by Virtual Influencer	Participated in Influencer Promotion	Purchase Frequency
1	Sneakers	399	Nike	Yes	Yes	3
2	Cosmetics	299	L'Oréal	No	No	1
3	Electronics	1999	Apple	Yes	No	2
4	Clothing	450	Zara	No	No	4
5	Cosmetics	320	Estée Lauder	Yes	Yes	2
6	Mobile Phone	3800	Samsung	Yes	No	1
7	Accessories	150	Pandora	No	No	5

Table 2 records consumer purchasing behavior data, including the types of products purchased, the purchase amount, whether they are influenced by virtual influencers, etc., aiming to analyze the degree of influence of virtual influencers on consumer purchasing decisions.

2.2. Data cleaning and preprocessing

In the data processing stage, the first task is to remove duplicate user data and comment content to ensure the accuracy and validity of the data. This process involves a detailed inspection of multiple interaction records of the same consumer, and by comparing user identification information, multiple records are merged into a single user unique identification to avoid repeated data calculation. Meaningless or unparseable comment content (such as garbled or blank comments) is eliminated. Invalid or abnormal data in interactive behavior (such as empty comments or abnormal likes data) is eliminated to ensure the accuracy of the analysis results. To analyze the trend of consumer behavior, the timestamps of all data are uniformly formatted and classified according to different time periods (such as days, weeks, and months) for time series analysis.

The X-axis of the left sub-graph of **Figure 1** shows the gender group of consumers, and the Y-axis represents the purchase amount of each consumer. It can be seen that the median purchase amount of female consumers is slightly higher than that of male consumers, which may mean that female consumers are more inclined to buy products endorsed by virtual influencers. The X-axis of the right sub-graph shows the age groups of consumers, which are divided into 4 intervals: 18–25, 26–35, 36–45, and 46–55, and the Y-axis represents the frequency of consumers' interaction with virtual influencers (such as likes, comments, shares, etc.). The younger age group (18–25 years old) may have a higher interaction frequency.

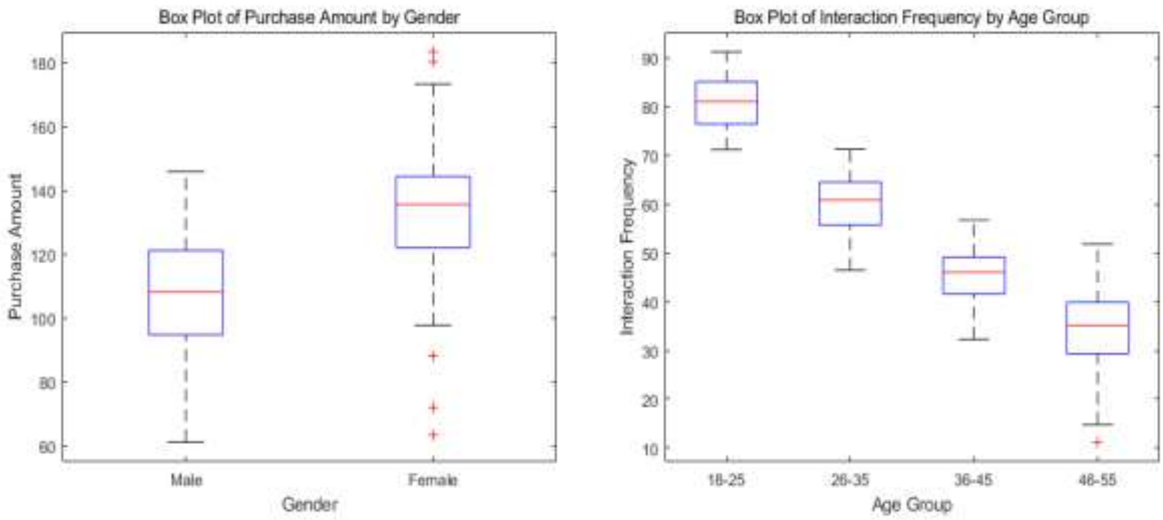

Figure 1. Distribution of different consumer groups in terms of interaction frequency or purchase amount.

2.3. Characteristic extraction and construction of consumer behavior dataset

The key consumer behavior characteristics are extracted after the data preprocessing work is completed. These characteristics specifically include: The total frequency of consumers' interaction with virtual influencers in a specific period of time, which includes likes, comments, and shares. This indicator intuitively reflects the consumer's attention and participation in virtual influencers. The relevant technology is used to extract the consumer's sentiment tendency score through in-depth sentiment analysis of the comment content. These scores are divided according to the three dimensions of positive, negative, and neutral, which effectively reveals the degree of emotional resonance of consumers with virtual influencers and their content. Based on the consumer's purchase history, the purchase frequency and consumption amount of the virtual influencer endorsed products are further calculated. These two indicators together reflect the consumer's acceptance and purchase intention of the virtual influencer recommended products. In addition, the consumer's personal influence on the social platform is also evaluated. The specific indicators include the number of times their content is shared and forwarded. These data can reflect the consumer's ability to spread the virtual influencer content and the coverage of the social network from the side.

A consumer behavior dataset containing multi-dimensional information is constructed by integrating the above characteristics. In this dataset, each consumer corresponds to a unique behavior vector, comprehensively covering key indicators such as interaction frequency, emotional tendency, purchase intention, and social platform influence, providing rich data support for subsequent analysis and modeling.

2.4. Integration of purchase records

To deeply explore the comprehensive impact of social media behavior on consumer purchase decisions, this study combines purchase record data to construct a complete consumer behavior dataset. The collection and processing of purchase record data specifically covers the following aspects:

First, the purchase frequency of each consumer in a specific time period (such as 30 days or 60 days) is counted. This data provides a basis for evaluating consumers' continued interest in virtual influencer recommended products. Subsequently, the cumulative purchase amount of consumers in the same time period is calculated, and combined with their interactive behaviors on social media (such as likes, comments, etc.) and emotional tendencies, the possible inherent connection between the purchase amount and the interaction frequency and emotional response is deeply analyzed, aiming to reveal the potential driving effect of social media activities on consumer spending. In addition, through a detailed analysis of consumer purchase history, the information of virtual influencer endorsed brands that they prefer is extracted. Specifically, by calculating the proportion of each consumer's purchase of virtual influencer endorsed products in the total purchase volume, the degree of consumer recognition and preference for virtual influencer endorsed brands is further quantified. This series of data processing processes lays a solid foundation for the subsequent in-depth study of the relationship between social media behavior and consumer purchase decisions.

3. Consumer group segmentation

3.1. Application of DBSCAN clustering algorithm

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is an advanced clustering method that automatically divides groups based on the density distribution of data points and has the ability to effectively handle noise data. In the scenario of consumer group segmentation, DBSCAN shows significant advantages because it does not require the number of groups to be set in advance and can accurately identify abnormal consumers (that is, noise points). When using this algorithm, the key implementation steps include:

In this study, Euclidean distance is used to measure the similarity between consumer behavior characteristics. Assuming that the behavior characteristics of each consumer are represented by a vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{in})$, where x_{ij} is the value of the i-th consumer on the j-th behavior characteristic (such as the number of likes, the number of comments, the purchase frequency, etc.). The Euclidean distance calculation equation is as follows:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{1}$$

Among them, $d(x_i, x_j)$ is the Euclidean distance between consumer i and consumer j, and n is the dimension of the consumer behavior characteristic. By calculating the distance matrix between all consumers, the DBSCAN algorithm can divide groups according to similarity.

The core parameters of the DBSCAN algorithm include Epsilon (ε), which defines the maximum distance within the density neighborhood. Small ε values lead to over-fine group division, while large ε values may lead to over-aggregation. In this study, the ε value is optimized by the grid search method, and the stability of the clustering results is tested according to different parameter combinations. MinPts defines the minimum number of points in each group. This paper selects a more conservative value (such as 5) to ensure that each group has sufficient consumer representation.

3.2. Clustering results

After clustering, the behavioral characteristics of each consumer group are statistically analyzed, and the following key findings are obtained: Through the DBSCAN algorithm, several representative consumer groups are successfully identified. The behavioral characteristics of different groups are obviously different. For example, some groups tend to frequently participate in social media interactions (likes, comments, etc.), while other groups show a high concentration in purchasing behavior. For each consumer group, by calculating the mean and standard deviation of its characteristics, the significant differences in interaction frequency, emotional resonance, and purchase intention of different groups are deeply revealed. Some groups show a low frequency of likes and comments, but are accompanied by strong purchase intentions. Such consumer characteristics suggest that they have high consumption potential and can be regarded as high-value target customers. On the contrary, other groups show a high frequency of interaction, but relatively weak purchase intentions. Such consumers may be more inclined to "watch" rather than actually buy, so they can be classified as "voyeuristic" consumers.

Finally, with the help of the DBSCAN algorithm, five consumer groups with distinct characteristics are successfully divided. Each group shows unique characteristics regarding interactive behavior patterns, emotional resonance, and purchase intentions. The following is a summary of the five groups:

The high potential purchase group has a strong purchase intention, showing that they are a potential core customer group. Most members are 18–24 years old. They show high interest and purchase potential in virtual influencer endorsed products, especially when the interaction frequency is low, they can still show strong purchase behavior. Although the low activity high purchase group has a low interaction frequency on social media, their purchase intention is strong, showing that they are consumers with high purchase potential. Most of this group is 25–34 years old and usually has high expectations in brand awareness and product trust, so they may need more incentives to participate in the interaction. The active observation group shows high social media engagement (such as likes, comments, etc.), but lacks actual purchase behavior. Most members are 35–44 years old. They are highly engaged in the brands and content endorsed by virtual influencers. However, because they consider price, brand, and product more, their purchase decisions are relatively cautious, and more marketing intervention may be needed to promote purchases. The high interaction low purchase group shows extremely high interaction frequency (such as likes, comments, etc.) on social media, but their purchase intention is low. Most of these consumers are between 45 and 54 years old. They may only be interested in the content endorsed by virtual influencers and express their opinions through interaction, but lack actual purchasing behavior. Consumers in the noise group have a very low frequency of participation, which is manifested as occasional participation in interaction and a lack of obvious purchasing behavior or emotional resonance. Most consumers in the noise group are 55 years old and above. These consumers may be individuals who occasionally participate or have low activity on social media, so they are regarded as noise data.

Although behavioral characteristics such as likes, shares, and purchase records can provide a preliminary understanding of consumer behavior, these quantifiable behavioral indicators do not cover the deeper factors that influence consumer decisions. For example, psychological or socioeconomic factors such as consumer personality traits (extroversion vs. introversion), personal values (sustainability or brand ethics), and complex emotional responses (emotional complexity, beyond basic positive, neutral, or negative emotional states) may have a more profound impact on consumer behavior. Therefore, relying solely on these surface characteristics may lead to a one-sided understanding of certain groups' behavior and underestimate their potential.

Current analysis methods mainly focus on behavioral performance (interaction frequency and purchase behavior), but the psychological motivations behind these behaviors are not fully considered. The purchasing decisions of different consumer groups may not only be determined by factors such as interaction frequency or brand awareness, but also by individual psychological characteristics and lifestyles. For example, extroverted consumers may be more inclined to participate in virtual influencer endorsement interactions, while introverted consumers may be less involved, but their purchasing behavior may be more rational and have long-term value. In-depth research on these psychological factors can help brands better understand consumer needs and preferences, thereby conducting more precise marketing.

In addition to behavioral characteristics and psychological motivations, socioeconomic factors (income level, educational background, occupation type, etc.) may also play an important role in consumer behavior. For example, high-income groups may pay more attention to product quality and brand background, and tend to buy high-end products endorsed by virtual influencers, while low-income groups may pay more attention to price factors, and their purchase intentions are not easily influenced by virtual influencers. Incorporating these socioeconomic factors into the analysis framework may reveal more diverse consumer group characteristics, thereby providing more comprehensive data support for brand marketing.

4. Behavioral differences

4.1. Data preparation and grouping

Before starting the ANOVA (Analysis of Variance), the first step is to reasonably divide consumers into different groups based on their behavioral data. Thanks to the effective use of the DBSCAN algorithm in the previous stage, multiple consumer groups with similar interactive behaviors and purchasing patterns have been successfully identified. Therefore, this study uses these segmented groups as the core analysis units, aiming to deeply explore the differences in key behavioral characteristics of each group, such as emotional resonance, brand awareness, and purchase intention.

Specifically, the behavioral characteristics covered in the dataset include the following aspects. First, based on the application of sentiment analysis technology, the sentiment tendency score of each consumer towards the content related to virtual influencers is precisely extracted. This score is a quantitative reflection of consumer emotional feedback. The specific calculation method is to obtain the average value of the sentiment score in their interaction, thereby accurately measuring the degree of emotional resonance of consumers; Secondly, regarding consumers' awareness of brands endorsed by virtual influencers, this study obtains corresponding evaluation results through detailed statistics of their purchase records and brand preferences. This indicator not only reflects consumers' familiarity with the brand, but also indirectly reveals the brand's influence in the market and consumers' brand loyalty. Through the extraction and arrangement of the above behavioral characteristics, detailed data support is provided for subsequent variance analysis, ensuring the accuracy and reliability of the analysis results. Awareness is measured by consumers' purchase frequency of products recommended by virtual influencers and brand-related interaction data. Consumers' purchase intention is measured by analyzing their attention to and purchase frequency of products endorsed by virtual influencers. The purchase intention score is calculated by a weighted combination of consumers' interaction data and actual purchase records. These behavioral characteristics serve as dependent variables, while the categories of consumer groups serve as independent variables.

In **Figure 2**, the X-axis lists the consumer groups grouped by age group, and the Y-axis lists the behavioral characteristics to be analyzed, such as emotional resonance, brand awareness, and purchase intention. Compared with groups in other age groups, the 18–24 group has the highest emotional resonance score, which may be because they have more positive emotional feedback on virtual influencers or are more inclined to pay attention to brand content endorsed by virtual influencers. The 18–24 group also performs well in brand awareness, indicating that they are more likely to identify and trust brands endorsed by virtual influencers, and their purchase intention scores are also high, suggesting that they show a strong tendency to buy in virtual influencer promotions.

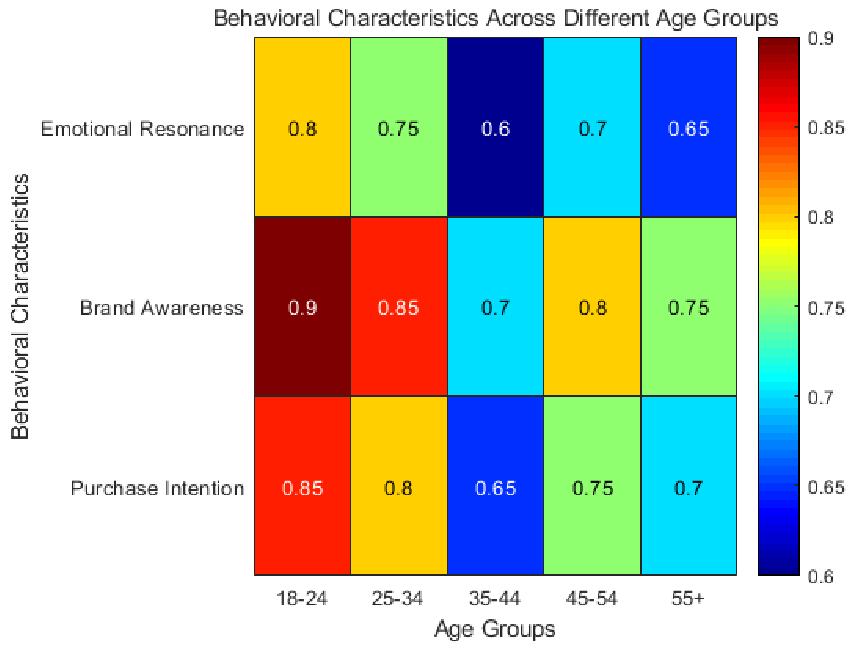

Figure 2. Correlation between groups and behavioral characteristics.

4.2. Implementation of ANOVA

This study uses one-factor analysis of variance to examine the emotional resonance, brand recognition and purchase intention of different consumer groups. The steps are as follows:

First, set the null hypothesis (H_0) and the alternative hypothesis (H_1). The null hypothesis states that there is no significant difference between the influence of virtual influencers and human influencers on emotional resonance, brand recognition and purchase intention among different consumer groups. The alternative hypothesis is that there are significant differences between virtual Internet celebrities and human Internet celebrities in the above three behavioral dimensions. During the specific analysis, in addition to focusing on the impact of virtual influencers, we will also compare the differences in the impact of virtual influencers and human influencers on consumer behavior especially on key indicators such as participation rate, emotional resonance and purchase intention. Next, each dependent variable (emotional resonance, brand awareness, purchase intention) is analyzed in groups according to consumer groups. Within each group, the mean and standard deviation of each behavioral dimension were calculated to assess behavioral differences between groups. Then, use the F test to calculate the ratio of the difference between groups to the difference within the group (F value). The larger the F value, the more significant the difference between groups, indicating that behavioral differences between consumer groups may be caused by the influence of virtual influencers or human influencers. If the p-value is less than 0.05, the null hypothesis is rejected and the difference between the groups is considered statistically significant.

4.3. ANOVA results and interpretation

During the variance analysis process of this study, the different impacts of virtual influencers and human influencers on consumer behavior were deeply explored, especially key indicators such as participation rate, emotional resonance and purchase intention. By analyzing the performance of different consumer groups on these dimensions, the following key findings were obtained:

The results of analysis of variance show that there are significant differences in the scores of different consumer groups on emotional resonance (F value is 5.26, p value is 0.002). In particular, those high-interaction groups (frequently participating in behaviors such as likes and comments) show stronger emotional resonance than low-interaction groups. This shows that whether it is a virtual Internet celebrity or a human Internet celebrity, a high frequency of interaction can significantly enhance consumers' emotional identification with the endorsement content, and the emotional communication effect of virtual Internet celebrities is particularly prominent among some groups.

The results of the ANOVA on brand awareness also revealed a significant difference (F value of 3.95, p value of 0.011). High purchase intention groups (consumers who frequently purchase products endorsed by virtual influencers) have significantly higher awareness of brands endorsed by virtual influencers than other groups. This shows that the brand promotion of virtual influencers plays a more effective role in brand promotion among certain consumer groups, especially those consumers who have already formed purchasing behavior.

In the analysis of purchase intention, the ANOVA results again showed significant differences (F value of 4.18, p value of 0.007). Groups with high interaction frequency and high emotional resonance have significantly higher purchase intentions than groups with low interaction frequency. This finding confirms the significant positive driving effects of emotional resonance and interaction frequency on purchase intention. Whether it is a virtual influencer or a human influencer, it can stimulate emotional resonance and prompt consumers to participate in frequent interactions, which will help increase their purchase intention.

Virtual influencers can trigger stronger emotional resonance through personalization, innovation and emotional connection with fans, especially among young people and high-interaction groups. In contrast, human influencers may have higher emotional resonance among certain groups (older groups or consumers with higher requirements for authenticity) due to their affinity and authenticity. Virtual influencers are great at increasing brand awareness, especially among younger demographics and early adopters. In contrast, human influencers may be relatively stable in increasing brand awareness, but due to the limitations of their personal images, they may not be able to achieve the explosive impact of virtual influencers on emerging brands or trendy products. In terms of driving purchase intention, virtual influencers have a significant role in promoting high interaction groups and high emotional resonance groups, especially in the short term, which can generate higher purchase intentions.

5. Structural equation model

5.1. Model construction

Based on an extensive literature review and a solid theoretical framework, this paper constructs a multivariate structural equation model to deeply analyze how virtual influencers affect consumers' purchase intention. The model specifically explains the following key causal paths:

As the core experience of consumers' interaction with virtual influencers, emotional response covers a variety of emotional tendencies, such as positive, negative, and neutral. The latent variable of emotional response is evaluated through specific quantitative indicators such as emotional scores and comment sentiment analysis in social media interactions, showing consumers' fluctuations and reactions at the emotional level. Trust, as another key dimension to measure the influence of virtual influencers, focuses on the degree of trust consumers have in virtual influencers and the brands they endorse. Its measurement basis is the brand loyalty and trust evaluation of consumers on virtual influencers, reflecting consumers' confidence and reliance on virtual influencers and the products they recommend. Brand awareness reflects consumers' understanding and memory depth of brands endorsed by virtual influencers. This factor comprehensively considers multiple dimensions, such as brand-related interaction frequency, purchase history, and consumers' attention to virtual influencers, revealing the status and influence of brands in consumers' minds. Purchase intention, as the core dependent variable in the model, reflects consumers' willingness to buy under the influence of virtual influencers. Its measurement indicators cover whether consumers intend to purchase products endorsed by virtual influencers, whether they participate in brand-related promotional activities, etc., which directly reflects the actual impact of virtual influencers on consumer behavior.

When constructing this model, this paper assumes that the three key variables of emotional response, trust, and brand awareness work together to affect consumers' purchase intention directly or indirectly. The complex interaction between them together constitutes the internal mechanism of virtual influencers influencing consumer behavior, providing theoretical support and an empirical path for an in-depth understanding of the marketing effect of virtual influencers.

5.2. Data preparation and measurement

The main steps of SEM (Structural Equation Modeling) modeling are as follows:

In the previous stage, social media interaction data (likes, comments, shares, etc.), purchase records, sentiment analysis results, etc., are integrated into a unified data framework. To ensure the accuracy of the measurement, the Likert scale is used to quantitatively evaluate consumers' emotional responses, trust, and brand awareness. Each variable is measured through multiple questions to ensure the reliability and validity of the measurement. All variables are standardized to avoid the impact of dimensional differences on model fitting. In this way, the estimates of different paths in the model can be kept within the same scale range, avoiding the impact of the scale of some variables being too large or too small.

5.3. Model fitting and path

After the data preparation is completed, the structural equation model is fitted using AMOS (Analysis of Moment Structures) software. The specific steps are as follows:

The constructed causal path is input into AMOS, and the potential relationship of each variable is set. Emotional response, trust, and brand awareness are used as independent variables, and purchase intention is used as the dependent variable. It is assumed that emotional response first affects purchase intention through trust and brand awareness, and there is also a direct path between trust and brand awareness. The maximum likelihood estimation (MLE) method is used for parameter estimation; each path's regression coefficients are calculated; each path's significance is evaluated. Through the path estimation results, the direct and indirect effects of each latent variable on purchase intention are tested.

The horizontal axis of **Figure 3** represents different age groups of consumers, and the vertical axis represents the goodness of fit index of the model. Through the analysis of the goodness of fit index, it is found that there are significant differences in the adaptability of different age groups of consumers to the virtual influencer marketing model. In all goodness of fit indicators, the 18–24 group performs better, with a smaller Chi-square (Chi-square Goodness of Fit Test) value, higher CFI (Comparative Fit Index) and TLI (Tucker-Lewis Index), and very low RMSEA (Root Mean Square Error of Approximation). Other ages are slightly insufficient in CFI and TLI, and Chi-square and RMSEA are high, suggesting that models and marketing strategies need to be optimized for different groups.

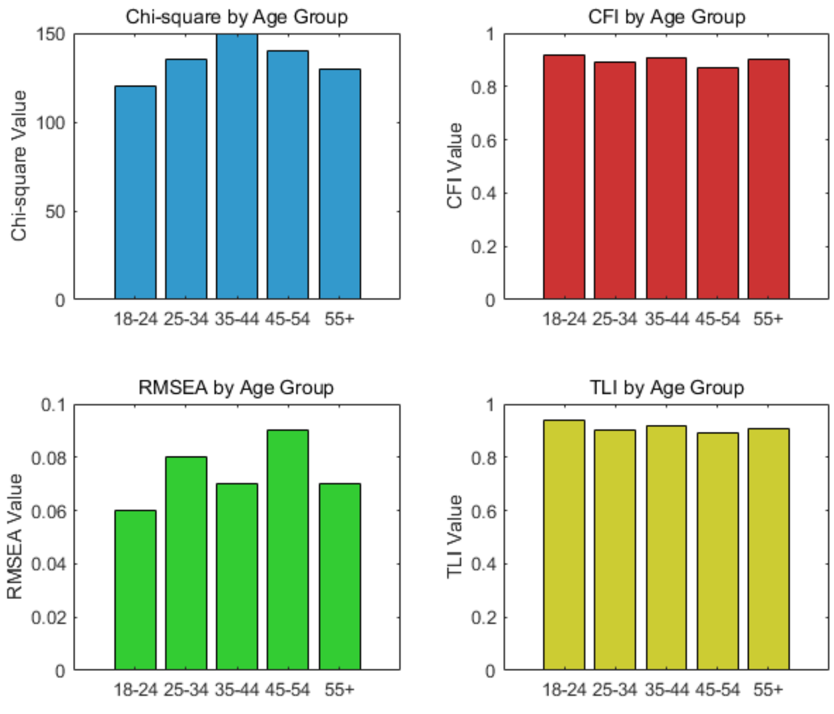

Figure 3. Model fitting of different consumer groups.

6. Evaluation

6.1. Differences in influence communication

The influence of virtual influencers on different groups varies in scope and intensity, and the diffusion effect of different groups in the process of virtual influencer communication is measured.

Using social network analysis methods, the communication paths of virtual influencers are tracked, and the breadth of communication among different consumer groups (such as the number of likes, comments, and shares, and the length of the communication chain) and the influence of different groups in the interaction are analyzed. Evaluation criteria: The average length of the communication paths of different groups, the forwarding rate, etc., are calculated, and the differences in communication intensity between groups are compared using multi-level regression analysis or social network analysis tools.

Figure 4 shows the differences in communication paths (number of forwardings) of different consumer groups in the process of virtual influencer communication. Through analysis, it is found that young people (18–24 years old) have stronger communication influence in virtual influencer communication, and their communication paths (number of forwardings) are longer. The number of forwardings all reach more than 25 times, indicating that their communication effect is better. Therefore, virtual influencer marketing strategies targeting younger groups may have a wider communication effect, while older groups may require different communication strategies to increase their engagement.

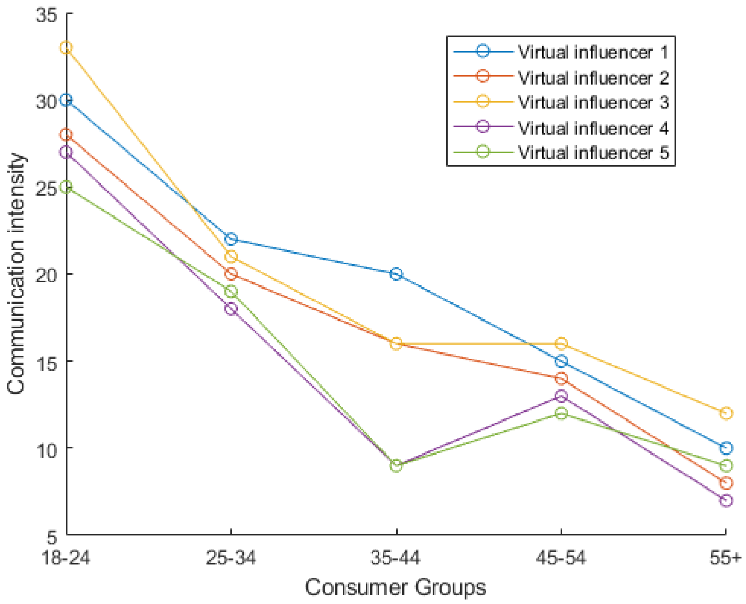

Figure 4. Differences in influence communication.

6.2. Consumer satisfaction

Consumers' overall satisfaction with virtual influencer endorsed products and brands is measured to understand the direct impact of virtual influencer promotion on consumer loyalty and brand identification. The consumer satisfaction is evaluated through a rating system.

Figure 5 shows the satisfaction of different consumer groups with products endorsed by influencers and those endorsed by non-influencers. The horizontal axis is the classification of consumer groups, and the vertical axis is the satisfaction score, ranging from 1 to 5 points. Young consumers (18–24 years old) have a higher satisfaction score of 4.2 points for products endorsed by influencers, indicating that they are more easily influenced by virtual or real influencers. Virtual influencers have a strong appeal among young groups because they are more inclined to interact with brands through social media and are more easily driven by fashion and trends on social media platforms. In contrast, older consumers (over 55 years old) show higher scores in satisfaction with products endorsed by non-influencers. This phenomenon may be related to their consumption preferences and brand loyalty. Older consumers may pay more attention to the long-term stability and brand reputation of products rather than the spokesperson effect.

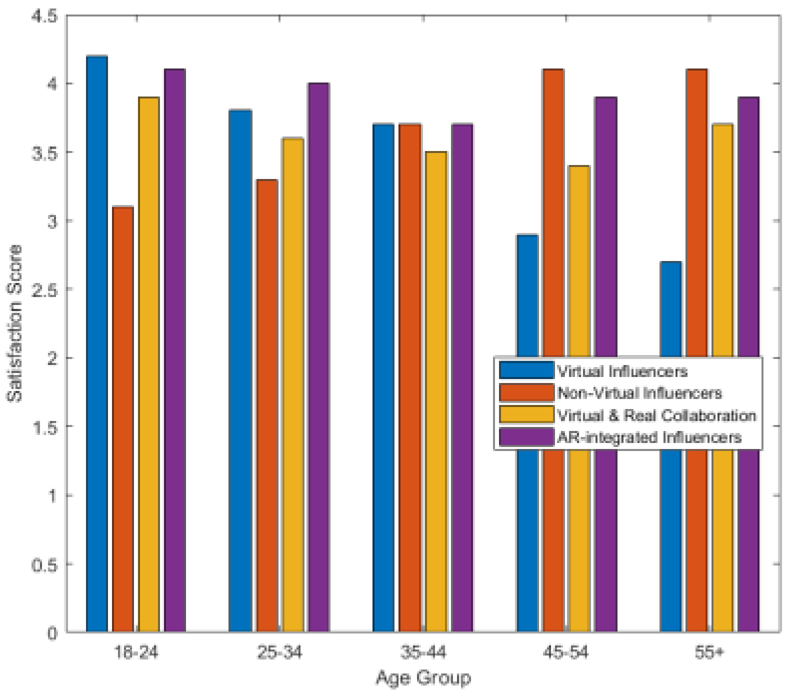

Figure 5. Consumer satisfaction.

The high satisfaction of young groups is closely related to the interactivity and innovation of virtual influencers, who can resonate with this group more accurately. Older groups may be more inclined to choose trustworthy brands or spokespersons rather than virtual influencers, especially for their accustomed consumer brands and purchase channels. Co-endorsement by virtual and real influencers can help expand a brand's audience and enhance brand influence by combining the strengths of both. In particular, among consumer groups with different endorsement preferences, joint endorsements can increase engagement and credibility. Influencers that blend real and virtual features may increase young people's engagement with real influencer endorsements, especially in the context of virtual influencer endorsements.

6.3. Differences in the persistence of virtual influencer effects

The duration of virtual influencers' influence in different consumer groups varies, measuring whether the influence weakens over time. Data collection over a long period of time allows comparison of consumer behavior in the short term (such as within 1 month) and the long term (such as after 6 months). Whether consumers continue to participate in virtual influencer interactive activities (including comments, sharing, etc.) and whether they maintain their purchase behavior of virtual influencer endorsement products are understood, as shown in **Table 3**.

Table 3. Persistence differences.

Consumer Group	Short-term Emotional Response	Long-term Emotional Response	Short-term Brand Recognition	Long-term Brand Recognition	Short-term Purchase Intention	Long-term Purchase Intention	Short-term Interaction Frequency	Long-term Interaction Frequency	Short-term Purchase Conversion Rate	Long-term Purchase Conversion Rate
18–24 years	4.3	3.5	4.2	3.7	4.5	3.8	4.8	3.9	25%	12%
25–34 years	4	3.4	4.1	3.6	4.3	3.6	4.5	3.8	22%	14%
35–44 years	3.7	3.2	3.8	3.3	3.9	3.4	4.2	3.5	18%	10%
45–54 years	3.5	3.1	3.7	3.2	3.8	3.3	4	3.4	16%	8%
55+ years	3.2	2.8	3.5	3.1	3.5	3	3.8	3.1	15%	5%

Table 3 reveals the differential effects of the virtual influencer effect on behavioral characteristics such as emotional response, brand awareness, and purchase intention in different consumer groups in the short term (within 1 month) and the long term (after 6 months). The results show that the persistence of the virtual influencer effect shows significant differences among consumer groups of different ages. Among young groups (18–24 years old), the influence of virtual influencers is particularly strong, but this influence is relatively short-lived. In the short term, virtual influencers can significantly increase brand awareness, stimulate consumers' purchase intentions, and trigger strong emotional reactions. However, over time, in the long term, these positive effects gradually weaken, and consumer engagement and purchase conversion rates show a downward trend. In contrast, in the 45–54 year old consumer group, the virtual influencer effect shows relatively persistent characteristics. The short-term influence of virtual influencers can be extended through a variety of strategies. Brands should focus on how to maintain contact with consumers through long-term content innovation and continuous interaction. For example: Virtual influencers can not only promote products through advertising, but also participate in content creation, and maintain long-term stickiness with the audience through regular live broadcasts, short videos or interactions with fans. Pure brand promotion may not be able to maintain consumer interest. Brands can design more interactive mechanisms (voting, challenges, Q&A, etc.) to let consumers feel the role of virtual influencers as a "participant" rather than just a "spokesperson".

7. Conclusions

By combining the DBSCAN algorithm with consumer behavior data, this paper successfully identifies five representative consumer groups and deeply analyzes the differences between these groups in terms of interactive behavior, emotional resonance, brand awareness, and purchase intention. Through cluster analysis, it is found that there are significant differences in the activity and purchase intention of different groups on social media, which provides an essential basis for formulating targeted marketing strategies. The paper also explores the influence dissemination path of virtual influencers in different groups, revealing that the dissemination effect of young groups is more significant. However, the shortcomings of this study are the limitations of group division and its behavioral characteristics. In the future, the accuracy of group segmentation and the effectiveness of marketing strategies can be further improved by applying more dimensional data and more sophisticated analysis methods. In addition, with the changes in the social media environment, attention should be paid to the differences in group behavior on different platforms and the long-term persistence of the virtual influencer effect.

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