Multidimensional Consumer Segmentation in AI Digital Human Image Adaptation: An Empirical Study of Age, Cultural Preferences, and Consumption Motivations

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https://doi.org/10.70695/10.70695/IAAI202503A8

Abstract

Starting from the perspective of consumer group classification, this paper explores the impact of age, cultural orientation, and consumer motivation on the adaptability of AI digital humans. Using data mining and regression methods, it presents the diverse demands of various consumer groups for digital human images. Empirical analysis reveals that age, cultural background, and consumer motivation significantly influence the formation of digital human image preferences. Younger groups are more receptive to interactive digital human images, while older groups tend to prefer designs that are both functional and practical. Cultural background and consumer motivations significantly influence consumer preferences. Global consumers have a high preference index for cultural identity, and social motivation generally ranks first among all groups. With these insights, this paper injects theoretical impetus into the optimized design of AI digital human images and points out practical paths for brand marketing strategies. The study further reveals that the design of digital human images needs to be personalized for consumers of different ages, cultural backgrounds, and motivations to improve the market acceptance of digital humans.

Keywords AI Digital Human; Consumer Segmentation; Age; Cultural Preference; Consumer Motivation; Preference Adaptation

1 Introduction

At the top of the digital wave, AI technology is rapidly rising and is profoundly changing human lifestyles and ways of interaction. What is particularly striking is that the interactive form of AI digital humans (virtual humans) has penetrated into multiple fields such as virtual customer service, online education, and entertainment media, becoming a bridge for communication between brands and consumers. According to data from the "China Artificial Intelligence Industry Development Report (2024)", the total market value of AI digital humans has reached a new level of 100 billion yuan, and the market growth prospects in 2026 are promising, showing huge potential for wide application across industries.

Although AI digital humans show significant application potential, a clear mismatch often exists between their designed image and consumer acceptance.Factors such as age, cultural background, and consumption motivation significantly influence consumers' cognition and acceptance of AI digital human images. The younger generation tends to choose digital images that are highly anthropomorphic and interactive, while older consumers prefer traditional and stable image design styles. Cultural background also plays a core role. Cultural differences are reflected in the inconsistency between the aesthetic and functional expectations of digital human images.

Implementing AI digital image adaptation solutions driven by consumer behavior clustering helps brands deeply analyze the needs of various consumer groups, thereby achieving accurate design and personalized services for digital human images. This article aims to analyze the impact of factors such as age, cultural preferences, and consumer motivations on the cognition and acceptance of AI digital human images through empirical analysis, providing theoretical support and practical guidance for brands to build digital human images and marketing strategies.

2 Literature Review

2.1 Concept and Characteristics of Digital Human

As virtual entities, digital humans are created using digital technology to reproduce human appearance, movements, and interactive traits. They are widely integrated into various virtual spaces and interactive systems. Lauer-Schmaltz et al. [1] have proposed that digital humans are not only virtual manifestations synthesized by computers, but also have perception and dynamic response characteristics similar to humans. With the help of human digital twin technology, the integration and interaction of virtual and reality can be achieved. Demirel et al. [2] assert that the core of the digital human model is its accurate mapping of human multidimensional characteristics, such as physiological structure, behavioral habits, etc., and through continuous interaction with the environment, it presents a human-like response pattern. Wang et al. [3-4] conducted an in-depth analysis of the application of HDT in the Industrial 5.0 era. The technology has significantly improved the efficiency of human-machine collaborative operations and promoted the application optimization of virtual individuals in complex physical environments. Song [5] analyzed the application of digital twins in the design industry, emphasizing the close integration of digital humans with the real environment, catalyzing design innovation and technological upgrades.

2.2 Consumer Behavior Segmentation Theory

The theoretical core of exploring how to differentiate groups based on consumer characteristics and behavior patterns, implement classification, and enhance the pertinence of market positioning and product promotion, Tohidi et al. [6] proposed to use the new behaviorist perspective to conduct a cluster study on the consumer groups in the organic food market, revealing the differentiated dimensions of organic food consumer motivations, and different behavior patterns significantly influence consumer choices and preferences. Busalim et al. [7] believe that focusing on the sustainable fashion industry, the formation of consumer behavior classification is closely related to values and social responsibility. Different consumer groups show significant differences in environmental protection concepts and purchasing motivations. Given the differences in characteristics of each group, marketing strategies must be customized. Taghikhah et al. [8] analyzed the purchasing habits of organic product consumers and examined the evolution of organic product purchasing trends. Data analysis supported by theory helps to gain insights into the behavior patterns of different consumer groups.

Nguyen and Mogaji [9] combined green marketing theory and conducted an in-depth analysis of the evolution of consumer behavior in emerging economies. They believed that environmental factors should be taken into account when segmenting the market, and that consumers' cultural background and economic conditions should be integrated for analysis. This revealed that there were significant differences in the acceptance of green products among different consumer groups. Wongsaichia et al . [10] extended the theory of planned behavior and analyzed the potential impact of green diet on consumers' purchasing intention. Brands can use market segmentation technology to accurately capture different consumer motivation groups.

According to relevant academic discussions, consumers' perception of digital human image acceptance urgently needs to be deeply analyzed with the help of behavioral segmentation theory, especially in brand marketing and product promotion, to explore consumers' preferences and demand tendencies for digital human images and lay a theoretical foundation for digital human image design.

2.3 Digital Human Image Design and Adaptation

Digital human image design and its adaptability are key components of digital marketing and consumer interaction. This study explores how virtual images can be matched with the needs and preferences of consumer groups. Xu [11] proposed that digital media design should combine human-computer interaction and image processing to achieve more accurate human image replication, build emotional bonds, and thus deepen user interaction experience. In 2024, researchers such as Fu et al . [12] analyzed adaptive multimodal control in digital human hand motion synthesis, emphasizing that the precision and dynamic feedback of digital human images are crucial to improving consumer engagement and interactive experience. According to the research of Silva and Bonetti [13] , the application of digital humans in the fashion industry requires not only precise image design, but also the understanding of consumers' concerns and expectations for virtual image interaction. Especially in brand marketing, the fit between digital human images and brand marketing has a direct impact on their attractiveness and persuasiveness.

Holzinger et al. [14] emphasized that in the tide of digital transformation, strengthening humanization and digital human image design should be given priority, especially in the complex architecture of intelligent systems. The imaged digital should demonstrate the ability to adapt to the environment and match needs. Based on the research of Fu et al. [15] , it is further proposed that by using cutting-edge technologies such as StyleGAN, the digital human image construction process can be optimized with the help of data-driven strategies to enhance the realism and personalized attributes of the virtual image.

The above research reveals that the success of digital human image design does not rely solely on the depth of anthropomorphism. It implements precise matching strategies based on differences in consumer culture, age, and consumption motivations, and explores the needs of different consumer groups for the adaptability of digital human images. The research is of far-reaching significance and helps brands build a scientific foundation for digital marketing strategies.

3 Research Design and Model Construction

3.1 Research Methods and Data Sources

This study uses quantitative analysis to construct an AI avatar adaptation architecture based on the database of the "What matters to today's consumers 2024" report released by Capgemini Research Institute in 2024. This dataset collects survey data from 11,681 consumers worldwide, covering multiple variables such as age, cultural preferences, and consumption motivations .

During data preprocessing, mean imputation was initially used to fill in missing data and maintain data completeness. Box plots were used to identify and remove abnormal values to improve data quality and reliability. Z-score standardization was implemented on numerical variables to eliminate systematic bias caused by dimensional differences and maintain consistency in the variable analysis scale. Table 1 shows the local data set after data preprocessing, which shows the distribution of consumers' age groups, cultural backgrounds, consumption motivations, and preference scores for AI digital human images (1-5 points):

Table 1. Part of the data after preprocessing

Consumer ID	Age Group	Cultural Background	Consumption Motivation	AI Digital Human Preference
001	Gen Z	Local	Functional	4
002	Millennials	Global	Emotional	5
003	Gen X	Local	Social	3
004	Boomers	Global	Functional	2
005	Gen Z	Local	Emotional	5
006	Millennials	Global	Social	4
007	Gen X	Local	Functional	3
008	Boomers	Global	Emotional	2

Through in-depth analysis of these data, we can analyze the inherent fit between consumer attributes and AI digital image tendencies, and lay the theoretical foundation for digital human image design.

3.2 Theoretical Model and Hypothesis

Segmentation Model Based on Consumer Age, Cultural Preferences, and Consumption Motivations

To further reveal the differences in preferences of different consumer groups for AI digital human images, this section focuses on three core variables: age, cultural orientation, and consumer motivation. We construct a clustering model to segment consumer groups and define vectors $\mathbf{x}_j = \left(x_{1j}, x_{2j}, x_{3j}\right)$. x_{1j} The variable indicates the age group of the jth consumer. x_{2j} The value reflects the individual's belonging position in local and global cultural identity. x_{3j} The score reflects the consumption motivation, including functional, emotional, and social dimensions. Then, the K-means clustering algorithm is implemented to form a grouping model, striving to minimize the sum of squared errors within the cluster, that is:

$$\min_{\{\mu_i\}_{i=1}^{k}} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in C_i} \| \mathbf{x}_j - \mu_i \|^2 \tag{1}$$

Where C_i is the symbol for cluster μ_i i , is the coordinate of the cluster's centroid, and k is the number of clusters . Cluster centers and sample distributions are repeatedly calculated to maximize intra-cluster homogeneity. To ensure model stability, features are normalized, and variances are standardized to 1. Clustering is complete, and clustering effectiveness is analyzed using the silhouette coefficient. A silhouette coefficient exceeding 0.5 indicates a good clustering result. The model can identify consumer groups with similar consumption habits, providing personalized support for subsequent digital human avatar customization. Figure 1 shows the distribution pattern of consumer groups clustered by age, cultural orientation, and consumption motivation using the K-means algorithm. Principal component analysis (PCA) is used to reduce three-dimensional attributes to a two-dimensional level. Color-coded clusters facilitate intuitive analysis of differences between groups:

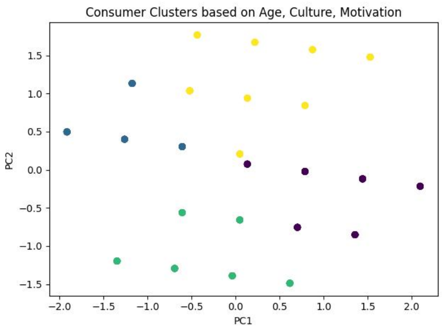

Fig. 1. Visualization of clustering model

Construction of AI Digital Human Image Adaptation Model

After clarifying the clustering results, this section continues to build an AI digital human image matching model, detailing the specific impact of consumer attributes on digital human preferences. Using consumers' favorable opinions of digital human images as the dependent variable Y and age X_1 , cultural background X_2 , and consumer motivation as independent X variables, this section comprehensively examines the strength and direction of each factor's influence and conducts multivariate linear correlation analysis:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \tag{2}$$

Among them β_0 , is the basis of constants, $\beta_1, \beta_2, \beta_3$ which constitutes the regression coefficient group of independent variables, ε is the random error term , $\text{ā}(\varepsilon) = 0$ and $Var(\varepsilon) = \sigma^2$ the coefficient vector is obtained by the least squares method . The significance of the model and its coefficients was evaluated using t-tests and F-tests. There may be interactive correlations between groups , and the combination of interactive effect variables can be introduced . The interactive effect X_1 X_3 , the interaction between age and consumption motivation, the model expansion is established:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 \left(X_1 X_3\right) + \varepsilon \tag{3}$$

To explore the differences in preferences for digital human images among different consumer motivation groups, the model evaluation concluded, and residual and collinearity tests were conducted on the model to verify its rationality. Based on the sign and value of the coefficients, the positive and negative effects and strength of consumer characteristic variables on preferences for AI digital human images were analyzed to guide digital marketing practices. Figure 2 shows the scatter distribution of the actual and predicted preference scores of the linear regression model, revealing the model adaptation effect and error distribution:

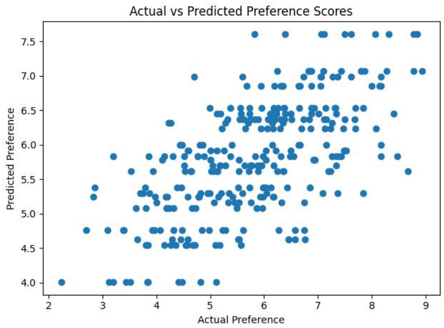

Fig. 2. Visualization of the adapted model

3.3 Research Variables and Measurements

The analysis variables included consumer age, cultural orientation, consumer motivation, and preference evaluation of AI digital human images. Consumers were divided into four generations based on their birth year: the Z age group. The scale was structured in an ordinal manner. The questionnaire examined consumers' identification with local and global cultures. A value of zero represented a fundamental sense of belonging to local culture, indicating a preference for global culture. This was categorized as a binary nominal variable. When studying consumer motivations, the three major motivation types of functional, emotional, and social were used as the analytical framework. Data was collected based on respondents' selection of their primary motivations. M=1 was used to indicate functional characteristics, M=2 for emotional motivation, and M=3 for sociability. This was categorized as a multivariate nominal variable. The preferred evaluation object was the AI digital human image. A seven-point Likert scale was used for scoring. This was categorized as a continuous variable.

The reliability and validity analysis of the scale was carried out, and the multidimensional aspects of consumer motivation and preference scores were verified through internal consistency tests and aggregation indicators. The Cronbach α coefficient was calculated as follows:

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_t^2}\right) \tag{4}$$

Here, the number of dimension measurement items is recorded as k , σ_i^2 that is, the fluctuation variance of the i- th item, the total scale variance σ_t^2 , the confirmatory factor analysis results, which are reflected in the formula expression of combined reliability, composite reliability, and reliability combination:

$$CR = \frac{\left(\sum_{i=1}^{n}\lambda_i\right)^2}{\left(\sum_{i=1}^{n}\lambda_i\right)^2+\sum_{i=1}^{n}\theta_i} \tag{5}$$

Among them, the factor loading factor of each measurement item is recorded as λ_i , θ_i which is the variance parameter of the error term. When calculating AVE, the formula is used $AVE = \frac{\sum_{i=1}^{n}\lambda_i^2}{\sum_{i=1}^{n}\lambda_i^2+\sum_{i=1}^{n}\theta_i}$ to evaluate the cluster validity coefficient. CR The value is over 0.70 and the AVE value is over 0.50. This scale shows a high level of cluster validity. In the data collection stage, it is necessary to assign dummy variables to nominal variables, mark cultural preference variables C_0 with , and classify C_1 consumption motivation variables M_1、M_2、M_3 to ensure that the regression model treats each category equally, as shown in Table 2:

Table 2. Variable settings

variable name	Measurement method	Scale type	Encoding method
Age group	Birth year groups (18–24, 25–40, 41–56, 57+)	Ordered classification	1=Gen Z, 2=Millennials, 3=X, 4=Baby Boomers
Cultural preferences	Degree of identification with local and global culture (both options)	Nominal variables	0=local culture, 1=global culture
consumption motivation	Functional motivation/emotional motivation/social motivation	Nominal variables	1=Functional, 2=Emotional, 3=Social
Digital Human Preference Rating	1–7 Likert scale	Continuous variables	Take the mean score as the dependent variable

4 Empirical Analysis and Results

4.1 Empirical Verification of Variable Relationships

The analysis variables included consumer age,4.1.1 The Impact of Age on AI Digital Human Image To analyze the impact

Of age on preferences for AI digital human images, the sample was divided into age groups by year of birth. Using statistical software such as SPSS/Python, the mean and fluctuation range of preference scores for each age group were measured. The data were simultaneously examined for normal distribution properties and variance equilibrium. During processing, invalid questionnaires were screened and outliers were verified. A one-way analysis of variance (ANOVA) was conducted to test the significance of age group differences in preferences. The F value showed significance, and the p value was far below the critical value of 0.05, revealing significant differences in preferences by age group. Table 3 and Figure 3 show the mean and fluctuation range of preferences for digital human images by age group. This age group had the highest mean score of 6.8, followed by the 18-24 age group, the 25-30 age group (6.6), and the 31-35 age group (6.4). Preference scores gradually decreased with age, with the 56-year-old and older group scoring only 4.8. As age increases, the standard deviation decreases slightly. The evaluation of the older group shows convergence. The young group grows up in the fertile soil of digitalization and has a high frequency of acceptance and use of virtual images. The middle-aged and elderly groups have low awareness and trust in new technologies. The research results provide guidance for the implementation path of subsequent image design. For young users, it is advisable to strengthen the integration of interaction and entertainment. For elderly users, the focus should be on strengthening the functionality and trust of the product to enhance the level of acceptance.

Table 3. The impact of age on digital human image preferences (n=6,850)

Age group (years)	Number of samples	Mean preference of AI digital human image	Standard deviation
18–24	850	6.8	1.1
25–30	900	6.6	1.0
31–35	950	6.4	1.0
36–40	900	6.1	0.9
41–45	850	5.7	0.8
46–50	800	5.4	0.7
51–55	800	5.1	0.6
56 and above	800	4.8	0.6

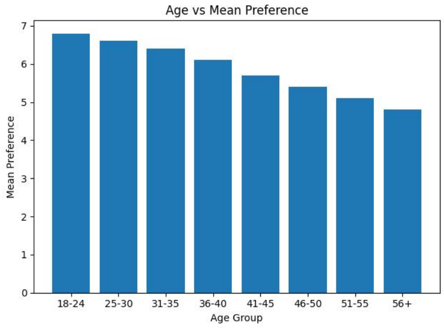

Fig. 3. Visualization of age and average preference

The Impact of Cultural Preferences on the Image of AI Digital Humans

Cultural orientation reveals consumers' level of identification with local and global culture, a factor that may influence their acceptance of digital avatars. This experiment divided participants into two categories based on their cultural orientation: "local" and "global." A cross-sectional examination was conducted across age groups and cultural backgrounds. Initially, the cultural preference variable in the dataset was dummy-coded. Using cross-tabulations, a systematic analysis of the average preference scores across age groups within culturally diverse contexts was conducted. Independent sample t-tests and two-way ANOVA were then used to assess the interaction between cultural preference and age. Cultural orientation significantly influenced digital preferences. Those who identified with a global culture generally outperformed those who identified with a local culture across all age groups, with p-values below 0.05. The average scores for each age group paired with cultural orientation are plotted. Generation Z scored highest among the global culture group, while baby boomers, who identified with a local culture, scored lowest, at 4.9. The analysis process shows that there is an interaction between cultural background and age group: the score of local cultural members who are getting older decreases in direct proportion to the degree of age increase; even in the elderly group, those who identify with global culture have a good evaluation. The empirical results explain that in the scope of digital human image design, cultural symbols and adaptability requirements should be carefully explored, especially for the middle-aged and elderly groups with strong local cultural identity, regional cultural elements should be introduced to highlight the authenticity of the image and greatly improve its acceptability; focusing on young people with a global tendency, it is advisable to adopt innovative and diverse design concepts.

Table 4. The impact of cultural preferences on digital human image preferences (n=3,400)

Age group	Cultural preferences	Number of samples	Preference mean	Standard deviation
Gen Z	Global Culture	440	6.9	1.0
Gen Z	local culture	410	6.6	1.1
Millennials	Global Culture	460	6.7	1.0
Millennials	local culture	450	6.3	1.0
Gen X	Global Culture	420	6.0	0.9
Gen X	local culture	430	5.6	0.8
Boomers	Global Culture	400	5.5	0.7
Boomers	local culture	410	4.9	0.6

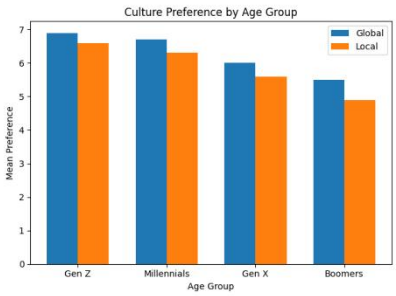

Fig. 4. Visualization of the impact of cultural preferences on digital humans

The Impact of Consumer Motivations on the Image of AI Digital Humans

Consumer behavior is guided by a core psychological force: consumer motivation. This study analyzes the effects of functional, emotional, and social dimensions on the shaping of digital human identities, further granularly analyzing them by age. Initially screening the consumer motivation categories in the questionnaire, respondents were categorized into their primary motivation groups. Intergroup mean comparisons and multivariate analysis of variance were conducted to explore the interactive impact of motivation type and age group differences. The charts (Table 5 and Figure 5) systematically display the average preference scores and standard deviations for the three consumer motivations across four age groups. The data, spanning twelve rows, show that across all age groups, the social motivation group consistently scores highest. Generation Z scored 6.9 for social motivation, compared to only 6.4 for functional motivation; emotional motivation falls somewhere in between. As age increases, preference scores for various motivations generally decrease. Even with this decrease, the gap between social motivation and other motivations remains significant, with test results revealing a significant difference ($p<0.05$). ANOVA analysis verified the rationality of the model through residual analysis, eliminating multicollinearity. When analyzing this phenomenon, social motivation highlights the desire for interpersonal communication and connection. AI digital humans, with their virtual interaction and companionship, are more aligned with the needs of this type of consumer. Emotional motivation focuses on aesthetics and experience, setting high standards for digital human image and verbal expression. Functional motivation focuses on practicality, resulting in limited attention to digital humans. Brands need to personalize and optimize digital human images based on consumer motivations, strengthening interactive attributes in social situations, emphasizing anthropomorphism and emotional expressiveness in emotional scenes, and enhancing effectiveness and credibility in functional scenarios to improve the overall user experience.

Table 5. The impact of consumer motivation and age group interaction on digital human preferences (n=3,540)

Age group	consumption motivation	Number of samples	Preference mean	Standard deviation
Gen Z	Functional	280	6.4	1.0
Gen Z	Emotionality	300	6.7	1.0
Gen Z	sociability	270	6.9	1.1
Millennials	Functional	290	6.2	0.9
Millennials	Emotionality	310	6.5	0.9
Millennials	sociability	320	6.8	1.0
Gen X	Functional	280	5.5	0.8
Gen X	Emotionality	290	5.8	0.8
Gen X	sociability	280	6.1	0.9
Boomers	Functional	270	5.1	0.7
Boomers	Emotionality	260	5.3	0.7
Boomers	sociability	280	5.7	0.8

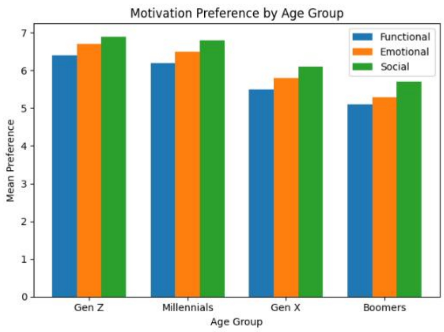

Fig. 5. Visualization of the impact of the interaction between consumption motivation and age group on digital human preferences

From the above analysis, it can be seen that age, cultural preferences and consumption motivations significantly affect consumers' cognition and acceptance of AI digital human images. The interaction between age and consumption motivation is significantly significant. The data foundation provides solid support for building accurate digital human image adaptation strategies.

4.2 Model Verification and Results Analysis

With model construction complete, to verify the significance of the impact of each factor and their interactions, multivariate analysis of variance was conducted to examine age, cultural orientation, consumer motivation, and their interactions. This sample set included 6,850 respondents. Initial inspections confirmed the normal distribution and variance consistency of preference scores, confirming the ANOVA prerequisites. Using statistical software, F-values and p-values were determined for each independent variable and interaction term. Partial effect size ($\eta^2 p$) was used to quantify the contribution of each factor to the overall variance. Age, cultural orientation, and consumer motivation significantly influenced digital human preferences, with consumer motivation having the highest F-value, indicating a particularly significant influence. The cross-influence of age, cultural preferences and consumption motivations is significant, and the interaction between age and cultural preferences, as well as between age and consumption motivations, is significant, revealing that different age groups have significant differences in their evaluation of digital people under the cultural or motivational background. The interaction test of cultural consumption motivation and the three-factor combination test were not significant, and the combination effect did not show additional significant signs. Table 6 presents the statistical test results of each factor and its interaction. The F value climbed, the p value decreased, and the significance increased significantly. The explanatory power of this factor on the total variance is proportional to the partial effect size. After systematic statistical testing, the significance of the core variables was confirmed, and the rationality of the model structure was verified, forming a solid foundation for subsequent in-depth analysis.

Table 6. ANOVA results of main effects and interaction effects (n=6,850)

effect	F-number	p-value	Significance determination	Partial effect size ($\eta^2 p$)
age	15.6	<0.001	significant	0.12
Cultural preferences	10.2	0.001	significant	0.08
consumption motivation	18.7	<0.001	significant	0.14
Age × Culture	5.4	0.005	significant	0.04
Age × Motivation	7.3	0.002	significant	0.06
Culture × Motivation	2.1	0.100	Not significant	0.02
Three-factor interaction	1.5	0.150	Not significant	0.01
Residual/Error	—	—	—	—

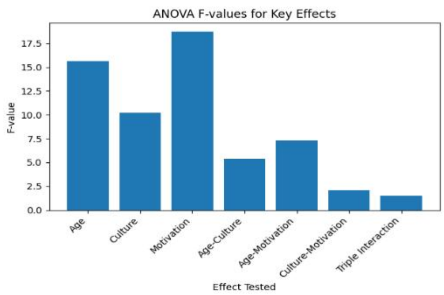

Fig. 6. F-values of main factors and interaction terms

Figure 6 shows the F-value distribution of each major factor and its interaction term, which allows intuitive identification of the size of the effect contribution and the difference in significance test. The values of consumption motivation and age dimensions are significantly ahead of other variables, and the model proves their criticality.

Different Consumer Responses to AI Digital Human Images

Given the significant confirmation of the core elements and their interaction effects, we carefully analyzed the differences in responses to digital human avatars across different consumer groups. Drawing on the aforementioned consumer segmentation criteria, we categorized the sample into eight consumer types: integrating age, cultural orientation, and consumer motivation. We constructed a multidimensional analysis matrix and, based on a regression model, numerically analyzed the group's predicted preference means. The observed means for each group were pooled, and the error between the predicted and actual values was analyzed to examine the model's fit. During sample preprocessing, the sample size for each group was verified to validate the reliability and validity of the statistical data.

Among the Generation Z group, which embraces a global culture and social motivation, the model predicted a preference score of 6.88, while the actual mean score was 6.90, a negligible difference of -0.02. Among the Millennial group, which embraces a local culture and functional motivation, the model's preference estimate was slightly overestimated, with a prediction error of 0.05, resulting in a slight difference between the predicted value of 6.25 and the actual value of 6.20. The difference between actual and predicted values remained within ±0.05, indicating a high degree of agreement between the model and actual data. Table 4.2.2 presents detailed data for the eight groups, which generally show a high preference for the social motivation and global culture combination, and a low preference for the local culture and functional motivation combination. Age differences within the different combinations are evident: Generation Z and Millennials generally show higher preference scores, while older generations (Generation X and Baby Boomers) have relatively lower scores. The analytical differences are evident, and the model accurately reveals the trends in consumer preferences for digital human avatars, recommending exclusive design and marketing solutions to brands.

Table 7. Comparison of Predicted and Actual Preferences of Consumer Types (n=3,540)

Age group	Cultural tendencies	consumption motivation	Predicted preference mean	Actual mean	difference
Gen Z	Global Culture	social contact	6.88	6.90	− 0.02
Gen Z	local culture	emotion	6.60	6.60	0.00
Millennials	Global Culture	social contact	6.79	6.78	0.01
Millennials	local culture	Function	6.25	6.20	0.05
Gen X	Global Culture	emotion	5.75	5.80	− 0.05
Gen X	local culture	social contact	6.05	6.10	− 0.05
Boomers	Global Culture	social contact	5.70	5.70	0.00
Boomers	local culture	Function	5.15	5.10	0.05

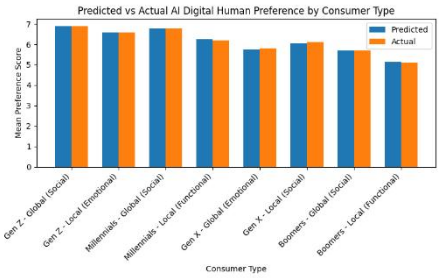

Fig. 7. Difference between predicted value and actual value

Figure 7 visualizes the difference between the predicted and actual data. The horizontal axis defines the eight consumer categories, and the vertical axis represents the preference scores. The two bar charts in this figure correspond to the model predictions and the actual observations, respectively. The differences between the groups are clearly visible, and the predicted values are highly consistent with the actual values, indicating that the model verification is very effective.

The analysis results reveal inconsistent responses among consumer groups to AI digital images, and also provide data evidence for marketing practices. During the digital human image shaping stage, customized adjustments should be implemented based on the complex combination of age structure, cultural preferences and consumer motivations. Among young and social groups, fun interactive experiences should be introduced, while the pursuit of functionality by older groups should be emphasized to strengthen their practicality and trust, thereby improving the overall acceptance of digital humans.

5 Conclusion

From the perspective of consumer group segmentation, this study examines the correlation between age, cultural preferences, and consumer motivations on the compatibility of AI avatars. By analyzing these consumer preferences and constructing regression models, this study reveals that the consumer demands that require attention in the field of digital human avatar design are diverse. The level of acceptance of digital human avatars is closely related to age, cultural identity, and consumer motivations. Younger generations, in particular, prefer highly anthropomorphic digital human avatars, while older generations prefer pragmatic designs. The interactive effect of cultural background and consumer motivations exhibits significant inconsistencies across consumer groups. Consumers with global cultural identities are generally open to digital human avatars, and social motivations are a common driving force across all consumer groups. This study offers theoretical guidance for digital marketing practices, clarifies strategies for optimizing digital human design based on consumer characteristics, and provides valuable insights for future research in this field.

Acknowledgement

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

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AI數字人形象適配中的多維消費者細分：基於年齡、文化偏好與消費動機的實證研究

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摘要：基於消費者羣體分類視角，本研究實證檢驗了年齡、文化取向與消費動機對AI虛擬形象適應性的影響機制。通過數據挖掘與回歸分析方法，揭示不同羣體對數字人形象的差異化需求。研究發現，年輕羣體對交互型數字人接受程度顯著高於年長羣體，而年長羣體普遍偏好功能實用型設計；文化背景顯著調節形象偏好，全球消費者對文化認可的偏好表現突出；社交動機在各羣體消費決策中均佔據主導地位。據此，本文為AI數字人形象的優化設計註入了理論動力，闡明數字人形象需針對羣體特徵實施個性化設計，為品牌營銷策略設計差異化路徑。

關鍵詞：AI數字人；消費者分羣；文化偏好；消費動機；偏好適配

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