# Analysis of Factors Influencing Consumption Willingness Among Target Customer Groups in the Chinese Nostalgia Market

**Boyuan Li, Qi Cheng, Wenjie Liao, Yuying Liang**

School of Management, Wuhan University of Technology, Wuhan, China

1529560024@qq.com, chengqi@whut.edu.cn, Liumankit0763@163.com, 1369851331@qq.com

**Keywords:** Nostalgic Consumption Market; Purchase Intention; Structural Equation Model; Integrated Learning; k-modes Clustering

**Abstract:** This study aims to deeply explore the target customer group portrait of the nostalgia consumption market and the factors influencing their purchase intention. The study finds that product design, functional value, nostalgic element differentiation and Internet marketing are the key factors influencing nostalgic consumption willingness, which provides important insights for nostalgic market development.

## 1. Introduction

Nostalgia consumption is an emerging consumption pattern in today's market, which refers to a consumption behavior in which people experience the past time by purchasing and using related goods or services. In the era of socio-cultural and economic changes, nostalgia can give people a sense of comfort and intimacy, and become a refuge in an insecure society [1].

Our country has always been recognized as a society that tends to be "past time oriented", as evidenced by its inhabitants' ancestor worship and strong family traditions [2]. Under the changing social environment, the sales of nostalgia-related products have increased dramatically, indicating that the nostalgia consumer market has a broad development prospect [3].

How to stand out from the crowd has become a challenge for companies selling nostalgic products to overcome. Based on this this survey hopes that by mining the influence factors of nostalgic consumption willingness of target customers in the market, so as to provide strategic suggestions for enterprises to carry out reasonable nostalgia marketing [4].

## 2. Analysis of Factors Influencing Nostalgic Consumption

### 2.1 Data Collection and Cleaning

This survey conducted searches on social media platforms such as Weibo, Zhihu, and Douban using keywords such as "nostalgic economy," "nostalgic consumption," and "nostalgic sentiments" to explore relevant discussions among the public. A web scraping program was developed in Python to extract the search results, yielding a total of 49,308 posts. The collected corpus underwent data cleansing, involving preliminary analysis and the removal of irrelevant terms to the central theme. Utilizing the cleaned data, high-frequency terms were identified. In addition to the search keyword "nostalgia," terms such as "old songs," "memories," "friends," "movies," "classics," "childhood," and "life" exhibited relatively high frequencies.

### 2.2 Sentiment Analysis

Through the cleansing and organization of the corpus, this survey obtained high-frequency words related to "nostalgic economy," "nostalgic consumption," and "nostalgic sentiments" on social media, providing an initial understanding of the public's primary points of interest. To further explore the emotional expressions of the public regarding topics related to "nostalgia," this investigation utilized the PaddleHub sentiment analysis model to analyze the sentiment tendencies of the collected corpus. This model is based on a bidirectional LSTM structure, capable of determining the sentiment polarity

  DOI: 10.25236/etmhs.2024.002

category of Chinese text, categorizing it into positive, negative, or neutral sentiments. The sentiment is quantified as a floating-point number between 0 and 1, where a value approaching 1 indicates a more positive sentiment, and a value nearing 0 suggests a more negative sentiment. The sentiment analysis results for a portion of the corpus are presented in Table.1.

Table 1 Partial Results of Sentiment Analysis

| Sentiment Polarity Classification | Example | Sentiment Score |
|---|---|---|
| Positive | Familiar taste, familiar recipe.As one ages, there is a tendency to appreciate a bit of nostalgia. | 0.999 |
| | I truly love nostalgia! | 0.998 |
| | I will surely lend strong support to products utilizing nostalgic marketing. | 0.993 |
| Neutral | With advancing age, the inclination towards nostalgia tends to grow; let's move forward on this long and winding road. | 0.494 |
| Negative | As someone like me can embrace nostalgia but won't look back. | 0.39 |
| | Nostalgic items are intangible; they will forever be locked in memories. | 0.263 |
| | "State-owned canteen" should refrain from overusing the gimmick of nostalgic marketing. | 0.013 |

Calculating the arithmetic mean of sentiment scores for the post collection yields a result of 0.865, indicating that the predominant sentiment category in textual data under the "nostalgia" related topics is mostly positive. Analysis of sentiment analysis results reveals that users predominantly express positive sentiments in nostalgic-related content on social media. This suggests that invoking consumer nostalgia for nostalgic marketing is feasible from an emotional standpoint [5]. While many users still find old products they once used attractive, it is crucial for companies engaging in nostalgic marketing to avoid using overly simplistic and aggressive advertising methods and refrain from overusing the gimmick of nostalgic marketing.

### 2.3 Semantic Network Analysis

To explore the relationships between high-frequency words and the structural connections among these terms, a semantic network model is established to investigate the co-occurrence relationships among high-frequency words. The semantic network graph takes the word "nostalgia" as the central node. The proximity of a word to the central node indicates a higher co-occurrence frequency with "nostalgia." According to the semantic network graph, words closely connected to the central node word "nostalgia" can be broadly categorized into three types, as detailed in Table.2.

Table 2 Analysis Results of the Semantic Network Model

| Category | Meaning |
|---|---|
| Category One | The first category comprises vocabulary primarily associated with tangible or cultural artifacts,including terms such as"snacks,""songs,""old songs,""movies,"and "artworks."These material or cultural products are closely tied to thepublic's nostalgia,capable of effectively eliciting nostalgic sentiments through similar mediums. |
| Category Two | The second category consists of words closely related to individuals,encompassing terms such as "youthful years,"era,""memory,""recollection,""childhood,""life,""everyone,"and "history."It is observed that cherished moments from the past,family,and friends evoke a stronger resonance among the public,consequently generating nostalgic emotions. |
| Category Three | The third category involves words related to style or marketing strategies,including terms such as "endorser,""nostalgicfeel,""emotion,""brand,""retro,""style,"and "story."These associated terms signify that the public can resonate with the nostalgic emotions conveyed by the product.In cases where brand,product design,advertising,and endorsers align with the audience's sentiments,a more effective stimulation of the target audience's nostalgia can be achieved. |

These three categories also represent different aspects for enterprises when developing the nostalgic consumption market.

The first category indicates the choice of media for nostalgic marketing by enterprises. Utilizing old items or cultural works can effectively evoke public nostalgia.

The second category emphasizes the selection of content for nostalgic marketing, closely connected with themes such as youth and history, thereby intensifying consumers' nostalgic sentiments.

The third category focuses on the choice of marketing strategies. The selection of endorsers, product design, and advertising with a retro style has a certain impact on consumers' decisions regarding nostalgic consumption behavior.

### 2.4 LDA Topic Model Analysis

In order to refine the themes of the content of the popular discussion and to facilitate the proposal of the subsequent research model and questionnaire design, this survey uses the LDA theme model to extract the themes of the textual data and analyze them. This survey uses theme consistency to determine the optimal number of themes. The higher the theme consistency, the better, representing the stronger differentiation between different themes, the final number of themes was determined to be 5. Modeling using the ldamodel class in the gensim library. The five themes are named as "design style", "food flavor", "cultural symbols", "past experience" and "literary works", which represent several discussion categories of the public when discussing "nostalgia" related topics.This survey has captured five major themes in the public discussion of content related to nostalgic consumption.

## 3. Consumer Differentiation Analysis and Potential User Exploration

In order to understand the basic characteristics of the respondents and achieve consumer differentiation analysis and potential user exploration, this survey first conducts a descriptive statistical analysis of the personal characteristics of the respondents. Next, a feature priority model is established based on the ensemble learning algorithm and CRITIC weighting, scoring the importance of individual features to explore the significance of different features for purchase intentions. Subsequently, differential analysis is performed on the sample data. Finally, the k-modes clustering algorithm is used, combining the results of differential analysis and the feature priority model, to segment the population into five categories of potential users.

### 3.1 Questionnaire Design

The overall consumption level in the central region of China is high, and the consumption forms are diverse. Wuhan, located in the central region of China, was selected as the research area due to its central position and the results of on-site investigations proving the development level of its nostalgic consumption market. Moreover, Wuhan serves as a major transportation hub, exerting significant influence on the surrounding areas. Therefore, Wuhan is representative for this study.

Survey Object: Urban residents in Wuhan

Survey Units: Every urban resident in Wuhan

The survey consists of three parts: The first part is the consumer differentiation survey, analyzing the importance of eight individual characteristics to purchase intentions through the feature priority model and selecting five key features for sample differential analysis. The second part is the investigation of potential users in the nostalgic consumption market. Based on the results of the first part, the k-modes algorithm is used to cluster five variables, measuring respondents' purchase intentions from three aspects: purchase willingness, premium purchase willingness, and repurchase willingness. The third part is the investigation of the influencing factors and paths of nostalgic consumption intentions. Through literature review, in-depth interviews, and social media data analysis, six aspects of nostalgic consumption influencing factors are investigated, and their impact paths are studied.

### 3.2 Feature Priority Ranking of Individual Characteristics

The AdaBoost algorithm is an adaptive boosting algorithm, and its adaptability is reflected in the following process: the weights of samples that were misclassified by the previous base classifier are increased, while the weights of correctly classified samples are decreased. These adjusted weights are then used to train the next base classifier. Additionally, in each iteration, a new weak classifier is introduced until a sufficiently low predetermined error rate or a specified maximum number of iterations is reached to determine the final strong classifier.

### 3.3 Consumer Differentiation Analysis

This study found through one-way ANOVA that there are significant differences in purchase intention and brand preference among consumers of different age groups. Through correlation analysis, it was found that there was a strong positive correlation between the intensity of personal nostalgia and purchase intention, a moderate positive correlation between the intensity of family nostalgia and purchase intention, and a weak positive correlation between the intensity of interpersonal nostalgia and purchase intention.

According to the results of feature ranking, seven variables, namely, age, highest education, monthly income, occupation, personal nostalgia strength, family nostalgia strength, and interpersonal nostalgia strength, were selected among all feature variables for consumer group clustering. Combining the feature prioritization model and user variability analysis, the the sample is subdivided into five categories of potential user groups: important potential users (26-35 years old, undergraduate, monthly income of 5,000-10,000 yuan), secondary potential users (36-45 years old, secondary school, monthly income of 5,000-10,000 yuan), general potential users (55 years old and above, secondary school), important development users (college students), and low-value users (36-45 years old, monthly income of 3,000 -5000 yuan).

## 4. Study on Factors Influencing Nostalgic Consumption Intentions

To investigate the mechanism and operational aspects of nostalgic consumption factors on purchase intentions, this survey formulates a theoretical model based on existing literature and employs a Structural Equation Model (SEM) for exploration, as shown in Fig.1.

### 4.1 Research Model

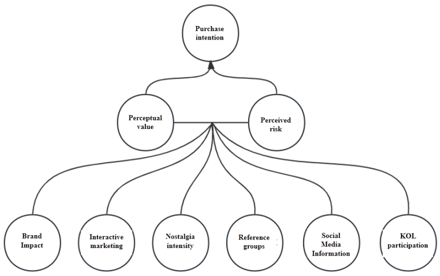


Fig.1 Research Model

This investigation employed text mining, in-depth interviews, and literature review to identify nostalgic consumption factors influencing purchase intentions. Based on these findings, a questionnaire was designed and its rationality was validated through a pre-survey. In the formal survey, principal component analysis was used to extract six nostalgic consumption factors. Finally, these six influencing factors were identified as exogenous variables, perceived value and perceived risk as mediating variables, and purchase intention as the outcome variable, forming the research model.

According to the research model and associated hypotheses, this survey utilized a Structural Equation Model to establish the theoretical model, as illustrated in Fig.2.

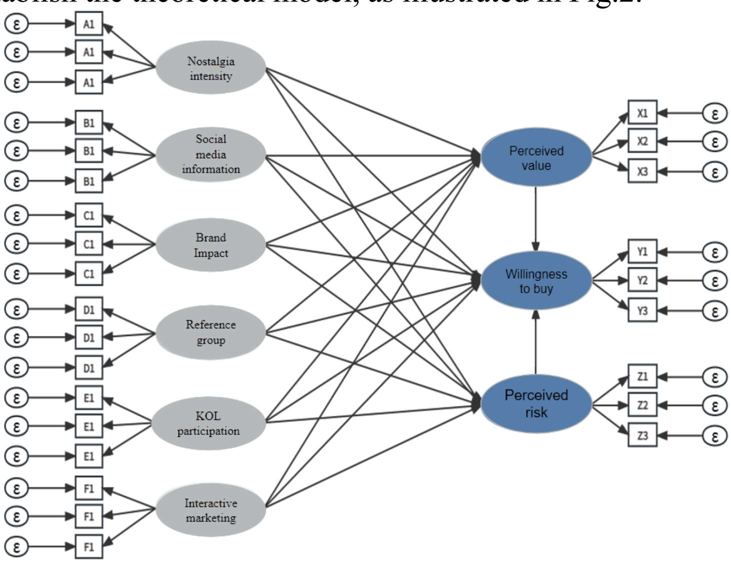


Fig.2 Structural Equation model

### 4.2 Purchase Intention and its Influencing Factors Modeling Analysis

Currently, there is no consensus in the academic community regarding the evaluation criteria for the fit of structural equation models. It is evident that a single indicator is insufficient to perfectly reflect the goodness of fit of the model. A comprehensive assessment requires the consideration of multiple indicators.

Taking into account perspectives from scholars such as Breckler (1990) [7], Hou, Wen, and Cheng (2004) [8], this survey chose to use the chi-square/degrees of freedom ratio, Comparative Fit Index (CFI), Non-Normed Fit Index (NNFI), Incremental Fit Index (IFI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA) as six indicators to assess the fit of the structural equation model.

The chi-square test can be used to judge the overall fit of the model. Generally, when the chi-square/degrees of freedom ratio is greater than 2 and less than 5, the fit of the established model can be considered acceptable. If the chi-square/degrees of freedom ratio is less than 2, it indicates that the model has an excellent fit [9].

Relative fit indices primarily reflect the degree to which the assumed model improves the fit compared to the baseline model. Typically, a relative fit index greater than 0.9 is considered indicative of excellent model fit.

In summary, the specific requirements for the six indices are summarized in Table.3.

Table 3 Structural Equation Model Fit Results

| Fitness index | Numerical value | Analysis of results |
|---|---|---|
| CMIN/DF | 2.884 | Good resulls |
| NNFI(TLI) | 0.954 | Outstanding resulls |
| CFI | 0.962 | Outstanding resuiis |
| IFI | 0.962 | Ouislanding results |
| RMSEA | 0.064 | Good results |
| SRMR | 0.058 | Good results |

### 4.3 Model corrections

After analyzing the results, if the fit indices of the equations are not satisfactory or do not reach a significant level, corresponding adjustments need to be made to the established model [10].

From the coefficient estimation results, it is evident that the path coefficients for Brand Influence on Perceived Value, Brand Influence on Perceived Risk, and Social Media Information on Perceived Risk did not pass the significance test. Therefore, these paths were removed, and additional paths were incorporated based on the recommended results from the software model adjustment.

The fit indices of the modified structural equation model are presented in Table.4.

Table 4 Fit Results of the Modified Structural Equation Model

| Fitness index | Numerical value | Analysis of results |
|---|---|---|
| CMIN/DF | 2.146 | Good resulls |
| NNFI(TLI) | 0.972 | Outstanding resulls |
| CFI | 0.977 | Outstanding resuiis |
| IFI | 0.977 | Ouislanding results |
| RMSEA | 0.050 | Good results |
| SRMR | 0.055 | Good results |

By comparing the model fitting results with those before the modification, it can be seen that the CMIN/DF, NNFI, GFI, CFI, IFI, RMSEA and SRMR fitting indexes have been improved accordingly, so it can be regarded that the present model is better fitted as a whole.

## 5. Conclusion

This study aimed to comprehensively and systematically explore the current state, influencing factors, and characteristics of the target demographic in China's nostalgia consumption market.

Through the utilization of web text mining methods, the analysis focused on public discussions related to nostalgia, examining content and sentiment trends. The findings revealed that a majority of internet users exhibit a positive emotional attitude towards nostalgia consumption, establishing an emotional foundation for businesses to engage in nostalgic marketing.The research identified key factors influencing consumer nostalgia consumption willingness, including product design style, manifestation of functional value, distinctiveness of nostalgic elements, and internet marketing strategies. Through a differential analysis of consumer personal characteristics, the study unveiled significant heterogeneity in nostalgia consumption willingness among different age groups, occupations, and income levels.In conclusion, the study constructed a theoretical model influencing nostalgia consumption purchasing intentions. Utilizing a structural equation model, the research validated the impact paths and mechanisms of factors such as brand influence, social media information, peer influence, interactive marketing strategies, opinion leader marketing, and individual nostalgia intensity on perceived value, perceived risk, and eventual purchasing intentions. This model provides theoretical guidance for the development of effective nostalgic marketing strategies, contributing to the sustained and healthy development of China's nostalgia consumption market.

## References


[1] Brown S, Kozinets R V, Sherry Jr J F. Teaching old brands new tricks: Retro branding and the revival of brand meaning[J]. Journal of marketing, 2003, 67(3): 19-33.

[2] Rindfleisch A, Burroughs J E, Wong N. The safety of objects: Materialism, existential insecurity, and brand connection[J]. Journal of consumer research, 2009, 36(1): 1-16.

[3] Stern B B. Historical and personal nostalgia in advertising text: The fin de siecle effect[J]. Journal of Advertising, 1992, 21(4): 11-22.

[4] Davis F. Yearning for yesterday: a sociology of nostalgia[J]. The collective memory reader, 2011, 5: 446-451.

[5] Holbrook M B. Nostalgia and consumption preferences: Some emerging patterns of consumer tastes[J]. Journal of Consumer research, 1993, 20(2): 245-256.

[6] Porter M E. Competitive advantage: creating and sustaining superior performance: with a new introduction[M]. Free Press, 1985.

[7] Bentler P. M., Comparative fit indices in structural models. Psychological Bulletin,1990.

[8] Sharma A, Foropon C. Green product attributes and green purchase behavior: A theory of planned behavior perspective with implications for circular economy[J]. Management Decision, 2019, 57(4): 1018-1042.

[9] Batcho K I. Nostalgia: A psychological perspective[J]. Perceptual and motor skills, 1995, 80(1): 131-143.

[10] Wood C M, Scheer L K. Incorporating perceived risk intomodels of consumer deal assessment and purchase intent[J]. Advances in Consumer Research, 1996.

[11] Chang C T, Feng C C. Bygone eras vs. the good Ol'days: how consumption context and self-construal influence nostalgic appeal selection[J]. International Journal of Advertising, 2016, 35(3): 589-615.