Economic Society and Humanities Vol. 3 No. 8, 2026

Research on Segmentation and Demand Differences of Generation Z Digital Financial Management Users Based on K-means Clustering

Yichen Lu, Guiling Zheng*, Zhixian He
Southeast University Cheng Xian College, Nanjing, Jiangsu, China
**Corresponding Author*

Abstract: The most prominent emerging generation in the market of digital wealth management is Generation Z with their specific tendencies in terms of financial activities, namely, early involvement age, social orientation and simplicity. However, the current wealth management system is highly homogenized, so there is an urgent need to segment users and understand their needs more deeply. This study targeted Generation Z and collected 1,002 valid questionnaires. This study has been able to determine six major clustering variables by incorporating the AIO/VALS theoretical framework and the K-means clustering algorithm to categorize the four types of users of the Generation Z namely rational-practical type, conservative-stable type, technology-dependent type and social-experience-oriented type as well as obtain a silhouette coefficient of 0.72 which shows that the cluster analysis was effective. According to the given analysis, it is suggested that the product comparison tools should be improved in case of the rational-practical group, incentive mechanisms; in the conservative-stable group, the emphasis is on the security and low-risk product development; in the technology-based group, the system of smart recommendations should be optimized, as well as the transaction costs reduced; in the social-experience-based group, it is necessary to design the community interaction features and a good user experience. These findings can provide data-driven empirical evidence and recommendations for online wealth management services, helping them implement tiered and precise operational strategies to fully leverage the advantages of product characteristics and marketing strategies.

Keywords: Generation Z; K-means Clustering; User Segmentation; Digital Finance; AIO/VALS Theory

1. Introduction

The digital economy and the popularity of the mobile internet are growing at an unprecedented rate, and as a result, generation Z is the new generation of people who are living in the internet world, which is the main force in the digital investment market. The number of the users of the Chinese Generation Z on the Internet has reached 300 million, and the percentage of those using it to manage their wealth is constantly increasing [1]. Previous researches have revealed that the current youth generation's attitude towards financial management and practices are changing with the introduction of the new technologies that have been associated with the use of the internet, social and entertainment activities. Financial management is not only a way to make money, but also a form of expression and communication [2], because financial management is no longer just a consideration of money. At the same time, Generation Z differs from other generations in terms of lifestyle, consumption habits, and financial investment preferences. Wealth management institutions need to fully consider these differences and shift from a product-centric service model to an online or scenario-based service model [3].

The members of the Generation Z are used to the internet, and they have a high level of familiarity with it. They do not have any problems in using it. Its main characteristics are as follows. As an age group that grew up in the Internet environment, Generation Z has several unique financial habits. For example, they take on financial responsibility at a younger age; they tend to use social media platforms to obtain information for purchasing or investing; and although individual investment amounts are small, their transaction frequency is extremely

high. For them, investing is not only a tool for making money, but also a way of life and an attitude towards life [4].

However, in the field of digital wealth management, products and business models have become highly homogenized. Most functions focus only on the transaction process and product presentation, with platforms paying less attention to service and feature design and instead focusing more on the transaction process and user experience—which is the key reason why they fail to meet the actual needs of Generation Z [5]. Such an imbalance between the supply and demand will result in low stickiness of users and retention rate of the platform as one of the major contradictions that prevent the development of the industry. Since the generation Z has a massive youth population, there are several questions about whether such groups exist in this group according to their financial principles and activities and what is the difference between the needs of various subgroups with regard to the performance of the functions and behavior of the members of these groups have become the main issues in the solution of the problem of the homogeneity of the industry and the operation of the platforms [6].

In the past few years, researchers have developed machine learning models that can be used for financial user segmentation. The results of the comparison between the performance of K-means and hierarchical clustering algorithms were based on credit card consumption data and it was concluded that the best number of clusters is four, which means that customers should be divided into four categories and thus the differentiated marketing could be quantitatively justified [7]. There are also some studies related to the robo-advisory where the authors used a customer profiling approach and designed the customer segmentation system on the basis of information about what customers buy in terms of wealth management products, which allowed them to identify the preferences and demands of various segments of customers [8]. These works offer references to this research paper as an application of K-means clustering in segmenting the Generation Z digital wealth management users. Nevertheless, they mostly studied their subjects of research being the credit card holders or the clients of the robo-advisory and the approaches to the study have not been applied to the case of the Generation Z digital wealth management yet.

The paper will concentrate on the above problems, where Generation Z people aged 18 to 28 who have experience in using digital wealth management platforms are used as research subjects and K-means clustering algorithm is applied to scientifically segment users with the aim of offering data support to the product design, marketing strategy, and user operations of digital wealth management platforms.

2. Research Design

2.1 Data Source and Sample Overview

The information is based on a questionnaire survey of Generation Z investors. This study surveyed Generation Z individuals aged 18-28 who had previously used digital wealth management platforms. A combination of stratified sampling and targeted online distribution was used, resulting in the collection of 1,002 valid questionnaires. The sample spans various cities. Out of the respondents, 41.7% were workplace newcomers between the age of 23 to 25 years, 38.6% were college students between the age of 18 to 22 years, and 62.4% were individuals with an average monthly disposable income of RMB 1,001 to 5,000.

2.2 Classification Indicators Selection According to the AIO/VALS Model

The AIO model and the VALS model are the two theories of consumer behavior that support the user segmentation. The concept of lifestyle differences was introduced by Wells and Tigert (1971) who recommended to define the difference in lifestyles of consumers with the help of three dimensions: activities, interests and opinions [9]. The values and resources oriented approach known as the VALS model segments the customers based on their value orientation [10]. It is a combination of these two and the logic of the value-based thinking of the group segmentation will be used as a conceptual framework of the study whereas the methodology of the choice of certain variables will be provided by the framework of the activities-interests-opinions of the AIO.

In particular, this paper converts the AIO/VALS model into three dimensions that are practically measurable. The first dimension is the investment behavior dimension, which corresponds to the activity dimension in the AIO model. This study focuses on users' actual behavior in financial management and selects

two indicators. Frequency of investments shows how much a user is involved in wealth management. High frequency investors will tend to demand intelligent features more than low frequency ones who might be more interested in safety and stability. The number of transactions each user makes reflects the amount of money they invest and directly affects their sensitivity to transaction fees and their expectations of product refunds.

The second aspect is the platform usage dimension, which can be transformed into the interest dimension in the AIO model. Users' attitudes and interests toward the wealth management platform are reflected through this dimension. This dimension reflects the degree of continuous user engagement on the platform: the user's stickiness index. It measures the intention of using the platform or not using it again and recommending the platform to other people, which will indicate the extent of recognition of the platform that the user has.

The third is the demand preference dimension, matching the opinions dimension of the AIO model. This metric reflects users' views and assessments of different platform functions. The degree to which users value security is related to their level of concern for fund security and risk disclosure, and it is also one of the key variables that distinguishes conservative users from aggressive users. Fee sensitivity relates to the level of concern of a user for transaction fees and return levels; highly sensitive users tend to perform rational price comparison, while less sensitive users might weigh other aspects of the experience more heavily.

Overall, the selection of these six indicators is based on the following three main factors. To begin with, theoretically, these six indicators are comprehensive in the three dimensions of AIO model which encompasses activities, interests and opinions as well as differences in values and resources of the VALS model, e.g. the level of security emphasis directly reflects a user's value orientation, while the amount of investment reflects the scale of a user's resources. Secondly, from the perspective of behavioral relevance, all six indicators are directly related to users' actual behavior on the wealth management platform, rather than being based on demographic characteristics, and therefore can more accurately reflect the essential differences between different user groups. Third, in terms of quantifiability of data, all the six indicators can be scored quantitatively using a Likert scale that satisfies the input data conditions of the K-means clustering algorithm.

Based on the above theory, this paper places the AIO/VALS three-dimensional model within three measurable dimensions: investment behavior, platform usage, and demand preferences, and selects a total of six core clustering variables. The specific selected variables are shown in Table 1.

Table 1. Core Clustering Variables

Theoretical Dimension	operationalizes dimension	Clustering Variable	Variable Meaning
Activities →	Investment Behavior	Investment Periodicity	The level of activeness of a user participation in financial investment
		Amount per Investment	the scale of user's capital input
Interests →	Platform Usage	Usage Duration	The stickiness of a user to the platform
		Platform Use Intention.	a user's inclination to endorse and keep using the platform
Opinions →	Demand Preference	Security Emphasis	The extent of fund security and risk disclosure that a user appreciates.
		Fee Sensitivity	The level of attention that a user pays to the transaction fees and levels of returns.

2.3 Data Preprocessing

To enhance the scientific and reliability of the clustering results, this paper used two steps of processing to raw data. The first step was outlier removal. To ensure that these extreme values do not affect the calculation of cluster centers, all extreme values that are too far from the mean of most samples are removed. The second one was standardization of data. Since the six variables are not measured on a similar scale and range of values e.g., frequency of investments is 1-5 points whereas the amount per investment is much larger. Inability to process the data would make those variables with greater values have an undue influence on the distance calculation. Thus, Z-score standardization technique was implemented to transform every variable into standardized data with mean zero and standard deviation of 1 so that all the variables could

contribute equally to the clustering procedure. After preprocessing, 1,002 valid samples were obtained for analysis.

3. K-means Cluster Analysis of the Generation Z Digital Financial Management User Groups

3.1 Determination of the Number of Cluster Groups

The clustering algorithm used in this paper is the K-means clustering, which was used to categorize the 1,002 valid samples. The iteration limit of the algorithm was fixed at 100 and the convergence rate of the algorithm was also limited to 0.0001 and the cluster centers were chosen at random.

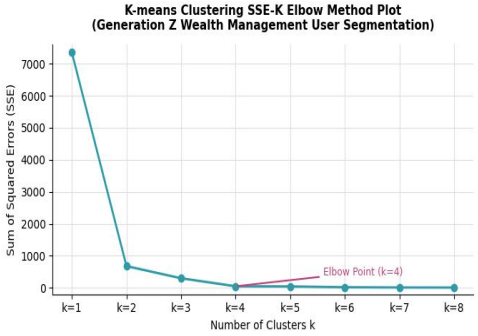


Figure 1. K-Means SSE-K Elbow Method Plot

The elbow method is used to determine the optimal number of clusters. The sum of squared errors was determined with the number of clusters ranging between 1 and 10, and a curve of SSE versus number of clusters was plotted. It is evident that the higher the number of clusters, the faster the SSE reduced; there was an obvious inflection point at 4 clusters, and after 4 clusters the rate of decrease in SSE became very slow. This led to the conclusion that it would be most suitable to divide the sample into four categories. As depicted in Figure 1, the clustering results are displayed.

3.2 Evaluation of Clustering Effectiveness

Once the clustering was done, the effectiveness of the clustering was determined by the silhouette coefficient that determines cohesion within clusters and separation between clusters. The higher the value, the better the clustering effect. The silhouette coefficient measured in this study was 0.72, as shown in Table 2 and Figure 2, indicating a good clustering effect. There is sufficient similarity among samples in each category and sufficient difference among categories. This finding is similar to the results of K-means clustering published in other researches. Customer segmentation studies based on user profiles have been proven effective in segmenting financial users using robo-advisors [8]. Compared with the above studies, the profile coefficient obtained in this study is 0.72, which is slightly higher than the threshold of 0.7 for "excellent" discriminant validity. This indicates that the six-variable clustering structure exhibits a satisfactory level of discriminant validity in the specific scenario of digital wealth management for Generation Z.

Table 2. Results of Silhouette Coefficient Test

Test Indicator	Value / Result	Indicator Description
Cluster count k	4	The best number of clusters found in this study
Silhouette Coefficient	0.72	Value > 0.7 means that there is a good clustering performance.
Meets require-ment	Yes	meets the research requirement of silhouette coefficient > 0.5
Silhouette coefficient rating	Excellent (>0.5)	Common industry standards rated.

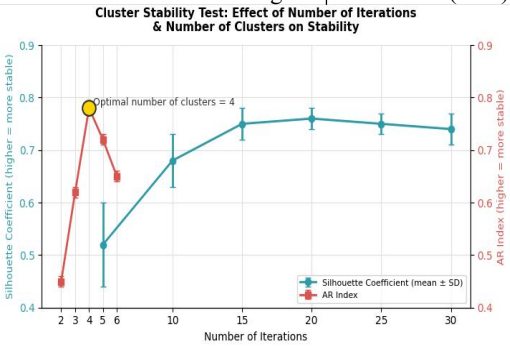


Figure 2. Cluster Stability Test

3.3 Characteristic Analysis of Cluster Groups Based on the K-Means Method

The survey data was analyzed using SPSS and a four-cluster analysis was conducted. The four groups were named based on the rating characteristics of each cluster center in the six variables, as well as the similarity of group members in terms of financial value and behavioral patterns. Table 3 provides a general description of the four groups.

Table 3. Summary of the Four Groups

Group Name	Sample Size	Proportion	Core Values	Investment Behaviour Characteristics
Rational-Practical	371	37.03%	pragmatism, rational decision making, cost effectiveness	moderate frequency, conservative decisions, focused on cost-benefit

			sensitivity	
Conservative-Stable	233	23.25%	safety-first, risk-averse, seeking stability	low frequency, modest amounts, a preference for low-risk products
Technology-dependent	237	23.65%	Technology-oriented, efficiency-focused, dependent on intelligent features	high frequency, familiar with features, actively explores new tools
Social-Experience-Based	161	16.07%	social orientation, values experience, willing to share	moderate frequency, values interaction, easily swayed by recommendations

The center of the cluster of the first group is characterized by an average level of investment frequency, medium amount of investments, relatively long period of use, high intention to use the platform, a rather high focus on the security and a relatively high sensitivity to fee. In general, they are logical and practical users who make their decisions carefully when it comes to investing, as well as concerned about the price of products and real results; therefore, such users were referred to as rational-practical type. This category consists of 371 individuals which is 37.03% of the total sample. The most significant number of people in this generation are the rational-practical types. Supplementary analysis using the table shows that these users do not follow any theory when making investment decisions, but rather base their decisions on pragmatic principles. They are not fads following people, but they have a tendency to compare the outcomes, cost and risks of various products and then decide on the one to buy. They are also quite interested in incentives provided by the platforms as part of their earnings as investors.

They are the users of wealth management platforms and they are also the ones that are not to be lost by the platform. This group has a relatively good performance in all of the demand indicators, with no particular shortcomings, and it has an average-to-high level of intelligent recommendation scores, as well as, ease of use, long-term use desire, and attention to the price of transactions.

The characteristics of the second type of cluster centers are: low investment frequency, low investment amount, moderate investment duration, medium to high willingness to use the platform, the highest requirement for security, and the lowest sensitivity to cost. These are people who are risk sensitive in terms of funds as they would rather be safe than sorry with their investments and are less willing to take risks. That was why they were called the conservative-stable type. The number of such individuals is 233 out of which 23.25% of them belong to the total sample.

Conservative-stable users are risk-averse and fund safety is their priority. They give the most attention to the completeness of risk disclosure, compliance qualification of the platform and measures of protection of funds. These investors invest relatively small amounts of money each time, invest relatively infrequently, and tend to choose low-risk products such as money market funds and short-term deposits. They are likely to remain on one platform that they trust in the long run and do not pay much attention to new intelligent features or socializing.

The characteristics of the third type of users are: high investment frequency, medium to large investment amount, longest usage time, highest willingness to use the platform, medium level of security concern, and highest sensitivity to fees. These users are also very demanding on intelligent features and ease of operation of the platform, familiar with digital tools, and like to try out new features; therefore they were referred to as technology-dependent type. This group included 237 participants, representing 23.65% of the total sample.

The typical digital natives are the users who rely on technology. They have a high level of financial literacy and the ability to use the platform in terms of its intelligence and recommendations, as well as the demand of the services that the platform can offer. These customers tend to make purchases quite often and they know the system fairly well and like experimenting with the new instruments.

The cluster center characteristics of the fourth type of users are: moderate investment frequency, small investment amount, short usage time, lowest willingness to use the platform, moderate emphasis on security, and lowest cost sensitivity. Social network and peer recommendation play a significant role in these users' investment decision making, and they expect a lot from the community interaction features of the platform; thus they were termed as social-experience-oriented type. This group consists of 161 persons,

that is, 16.07% of the sample.

The group of the smallest and most unique is the social-experience type. Users rely heavily on friends when making investment decisions because they need to leverage their friends' social networks and recommendations: for example, whether the platform has community features, supports portfolio sharing, and offers copy trading options. It does not mean that they don't need these services but it means that the present day platforms are focused mainly on the transaction of investments and there is no aspect of social interaction in them, which makes this particular group of people feel that they are not taken care of and satisfied. This category will be one of the key turning points of the platforms in order to operate in differentiated ways and is potentially rich in terms of development.

4. Recommendations for Customized Platform Services Based on Differences between Cluster Groups

According to the difference in characteristics of the four groups above, digital wealth management platforms can take tiered operating strategies, and design for the core needs of each group.

In the case of rational-practical group, platforms are to be concerned with increasing efficiency in decision-making and perceived gains. On the product level, multi-dimensional product comparison tools and automatic fee calculation features can assist users to easily compare returns, risks, and costs of various products, which will minimize time cost of information acquisition and making decisions. In terms of incentives, a tiered reward and points system can be established — including cash rebates, sign-in rewards, and membership rewards—to integrate incentive mechanisms into daily usage scenarios and give users a real sense of extra reward. At the portfolio of products, high-return low-fee packages of products can be introduced to strengthen the advantage of cost-effectiveness of the platform and meet the attention of this group on the input-output ratio.

For conservative and stable clients, building a strong brand image and ensuring security are paramount. Visual representations of security include adherence to platform compliance and information regarding fund custody and risk protection. At this stage, we recommend clients prioritize low-risk products such as money market funds, short-term deposits, and government bond reverse repurchase agreements. to the group, and secondly, they need to indicate the level of risk and the target audience at the product page. In order to maintain the service maintenance, it will be necessary to send reports of personal returns and updates of risk assessment, and even more so, when there is an abnormal fluctuation in the account, to inform the customer about the situation and provide explanations.

The technology-dependent group can also focus on intelligence and convenience. The intelligent features are the best to optimize, as the recommendation of products in the case of a user is done by an algorithm that needs to be more accurate and personalized, and it can be made dynamic according to the investment history of a particular user, his/her risk preference, and the scale of his/her capital. On the level of experience of operations, the elimination of unnecessary procedures during registration, verification, and transactions, and the possibility of one-click operation access to them will help increase the effectiveness of the overall process. In terms of cost control, the discounting scheme of fees with regard to the frequency of trades can be introduced in order to provide relief to the frequent traders who would have been paying high amounts of money on every trade [3].

Besides optimizing intelligent recommendations, platforms need to consider the cognitive features of young users as learning consumers, offer proper financial education and risk warnings, and avoid making technological convenience a catalyst for overtrading [11]. This perspective is particularly relevant for developing operational strategies for technology-dependent and socially experience-oriented groups.

For user groups who value social experience, relevant platforms should carry out differentiated innovations in user interaction and experience. At the community building level, functional areas such as financial management forums, investment experience sharing areas, and profit display boards can be set up to promote information exchange and experience sharing among users. At the social media level, sharing tools can be introduced to allow users to learn from the portfolio strategies of successful investors, thereby generating visually appealing personal investment experience cards that can be shared on platforms such as WeChat and Weibo. At the gamification level, mechanisms such as

wealth management challenges, growth level systems, and achievement systems can be introduced to transform financial management into a fun experience, thereby enhancing the sense of participation and belonging among the target user group.

5. Conclusion

The financial behavior of the new generation, namely Generation Z, is a fundamental and incremental element in the digital economy and financial technology that are closely related to each other; however, the fact that there is a high homogenization of the platforms on which the young people operate makes it challenging to identify the specific needs of this generation. The research was conducted using 1,002 questionnaires which were valid and used the AIO/VALS model as a theoretical background in selecting six variables: frequency of investments, amount invested per time, duration of use, intention of usage, focus on security and sensitivity to fees and then applied K-means clustering algorithm to cluster the users of Generation Z. The research classified the population of Generation Z into four types: rational-practical type, conservative-stable type, technology-dependent type, and social-experience-oriented type with the coefficient of clustering silhouette being 0.72, meaning that the clustering process was effective.

The four groups are quite separated in the demand factors like smart recommendation, convenience, desire to use the product over time, interest in the fees and incentives, as well as the attractiveness of the incentive system. The results of this study can provide scientific evidence and data support for digital wealth management services, helping them to gain a deeper understanding of user group characteristics, user differences, and the possibility of user segmentation. In a highly homogenized market environment, this will help the platform achieve more accurate positioning and engage in differentiated competition. This study also provides theoretical insights into how to develop inclusive finance and how to guide Generation Z to develop rational financial management behaviors.

Acknowledgments

This work is supported by the College Students' Innovation Training Program of Southeast University Chengxian College (No. XCX2026101).

References

[1] Wang Shuixiong. Observation of China's "Generation Z" Youth Group. People's Tribune, 2021(25): 24-27.

[2] Guo Jinlong. The Transformation and Characteristics of Young People's Financial Management Concepts and Behaviors. People's Tribune, 2024(1):80-83.

[3] Wealth Management Department, China CITIC Bank. Embracing "Generation Z": Creating a New Model of Digital and Scenario-Based Wealth Management. China Credit Card, 2024(9):77-80.

[4] Lu Jiehua, Zhang Yiyang, Li Lezhi. An Exploration of the Contemporary Characteristics and Heterogeneity of Financial Literacy among Youth. Youth Exploration, 2022(Online First): 1-14.

[5] Zhou Xiaochun, Zou Yuchun, Huang Jin. Financial Risks, Financial Capability and Social Work Intervention for Youth. Youth Studies, 2019(3): 69-81.

[6] Zhong Jingdong, Qin Xuezheng, Liu Chong. Internet Use, Financial Literacy and Financial Decision-Making: A Study Based on the China Household Finance Survey from 2013 to 2017. Economic Theory and Business Management, 2021(11): 68-78.

[7] Ge Yanna, Chen Chundi, Li Yanrong, et al. Research on Machine Learning-Driven Credit Card Customer Segmentation and Marketing. Modern Information Technology, 2026, 10(5): 90-94.

[8] An Yingbo, Zhou Huasen, Li Qing, Shen Chen, Kang Jie. Research on Robo-Advisory Services from the Perspective of User Profiling. China Management Informationization, 2025(9):90.

[9] Wells W D, Tigert D J. Activities, interests and opinions. Journal of Advertising Research, 1971, 11(4): 27-35.

[10] Solomon M R. Consumer behavior: Buying, having, and being. 13th ed. Boston: Pearson, 2019.

[11] Zhou Yi. An Analysis of the Behavioral Characteristics of Youth Consumption and Savings. People's Tribune, 2024(1):76-79.