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ANALYSIS OF GRASS-ROOTS BEHAVIOR AMONG YOUNG GROUPS

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Abstract: With the rise of the Internet and e-commerce, social platforms have integrated e-commerce into their ecosystems, giving rise to the "planting grass" culture. This paper examines the grass planting behavior of young users across different platforms. We conducted a literature review, designed a study using unequal probability three-stage sampling, and distributed 425 questionnaires, receiving 314 valid responses. Data was analyzed using descriptive statistics, cluster analysis, and a random forest model. Findings show that Little Red Book emphasizes practicality and authenticity but has inconsistencies between grass planting and purchasing. Tik Tok focuses on convenience and accuracy, with high consistency between planting and purchasing. Bilibili highlights professionalism, but users exhibit low purchasing frequency. Weibo users show inconsistent behavior and low usage frequency. Recommendations include enhancing consistency between planting and buying for Little Red Book, adopting user-specific strategies for Tik Tok, improving UP management for Bilibili, and diversifying methods for Weibo. Each platform has unique strengths and weaknesses. Long-term strategies and market research are essential for platforms to meet user needs and achieve rapid development.
Keywords: Grass platform; Unequal probability three-stage sampling; Random forest model; Cluster analysis

1 Introduction

According to the "50th Statistical Report on China's Internet Development," as of June 2022, the number of internet users in China reached 1.051 billion, with mobile internet users numbering 1.047 billion, accounting for 99.6%[1]. With the increasing number of internet users, the importance of mobile social networking in daily life has grown, and social media has rapidly risen[2]. In the era of social media, the media landscape has shifted from professional operations to global personal user participation, becoming a global sharing tool. Users utilize social media to establish virtual interpersonal relationships and achieve the integration of content production and consumption. Social media has surpassed traditional social functions, integrating business, social, and media resources to become a comprehensive platform.

Social platforms target the e-commerce market by attracting users through scenes, relationships, and content, making "planting grass" a crucial means of maintaining user growth. "Planting grass" content is widespread, influencing users' consumption decisions. Brands and merchants also use "planting grass" marketing to enhance user understanding and loyalty, thereby boosting sales. However, alongside "planting grass," there is also the phenomenon of "uprooting." Considering that young people are the main internet users with significant consumption potential, this paper studies the current situation of "planting grass" behavior among young users and provides targeted suggestions for social platforms.

Existing research primarily focuses on three aspects. First, research on "planting grass" marketing. Du Kangyi and Zhao Hongshan [3]pointed out issues in Xiaohongshu's marketing and provided suggestions; Jiang Jianguo and Chen Xiaoyu [4]discussed the problem of false marketing; Fu Donghan and Hu Li[5] suggested introducing industry KOLs, focusing on users' curiosity, and deepening user content; Wei Jiaxiao and Liang Yingtao[6], as well as Nie Luli[7], proposed strategies for optimizing short video KOL "planting grass" content; Li Zhongmei and Huang Min [8]studied Xiaohongshu's "planting grass" marketing strategies and provided countermeasures.

Secondly, consumer behavior research. Liu Siyu [9]used structural equation modeling to analyze survey data, finding that the affinity, professionalism, and reliability of "planters" positively influenced consumer interaction; Wang Shixin[10] used the Delphi method to extract and verify factors affecting consumers' "planting" and "uprooting"; Sun Yan[11] analyzed the transformation of user participation behavior from a participatory culture perspective; Fang Xuelan[12] studied the impact of the online "planting grass" landscape and called for rational treatment; Deng Sha[13] summarized the factors influencing consumers' purchase intentions through KOL "planting grass."

Lastly, research on "planting grass" culture. Hong Yu[14] explored the communication principles and issues behind the "planting grass economy" and proposed solutions; Lei Jinghui[15] studied the trust-building mechanisms in virtual sharing communities; Li Jiawen[16] analyzed the mechanisms behind "planting grass" culture; Dai Jiaqi and Xi Shizhen used the DART model and value co-creation theory to reveal the value co-creation mechanisms of "planting grass."

In summary, current research in China on "planting grass" mainly focuses on the content and optimization of "planting grass," consumer purchase intentions, and "planting grass" culture, with most studies taking Xiaohongshu as an example or focusing on KOLs. However, there is a lack of research on other mainstream "planting grass" platforms and user purchase decisions. Therefore, this paper attempts to explore the current situation of "planting grass" behavior among young users based on different "planting grass" platforms.

2 PRELIMINARY ANALYSIS OF THE SURVEY DATA

After completing the questionnaire design, we conducted a pilot distribution of the questionnaire to the young demographic based on the sampling frame. A total of 340 questionnaires were distributed and 340 were returned. After screening, 314 valid questionnaires were obtained. The collected data were then subjected to item analysis, as well as reliability and validity testing, to examine the discrimination of the questions, the reliability of the measurement results, and the validity of the questionnaire.

2.1 Item Discrimination Analysis

After collecting the questionnaires, we first analyzed the discrimination of each item on the scale. This was done to test the reliability of the scale and individual items. We used the high-low group mean difference test method. Items with low discrimination were excluded.

For the item analysis, we focused on Q22 (user satisfaction with TikTok). We summed the scores of all 9 items for each respondent, assigning the average score to any unanswered item. Respondents were then sorted by total score, with the top 27% as the high group and the bottom 27% as the low group. We performed an independent sample t-test on each item between the high and low groups. The t-values for all 9 items were significant ($p < 0.05$), indicating good discrimination.

Similarly, we analyzed Q23-Q25 for other platform users using the same method. The t-values for all items were significant ($p < 0.05$), indicating good discrimination.

In conclusion, the questionnaire passed the item analysis and is suitable for formal investigation.

2.2 Reliability Testing

Reliability testing of the questionnaire design refers to analyzing the accuracy of the measurement results, specifically evaluating the precision and consistency of data obtained from repeated use of the questionnaire. Reliability analysis reflects the true degree of the measured characteristics. We used Cronbach's alpha to measure the internal consistency of the questionnaire items, with the reliability coefficient ranging from [0,1]. The calculation formula for Cronbach's alpha is as follows:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum s_i^2}{s_T^2}\right) \tag{1}$$

In this context, k represents the total number of items in the scale, S_i^2 is the variance of the scores for item i, and S_T^2 is the variance of the total scores across all items. Cronbach's alpha evaluates the internal consistency of the scores across items in the scale. A higher Cronbach's alpha indicates greater reliability. Ideally, a well-designed questionnaire should have a reliability coefficient above 0.80. A coefficient between 0.70 and 0.80 is acceptable, but if the internal consistency of subscales is below 0.60 or the overall reliability is below 0.80, the questionnaire should be revised.

For this questionnaire, the Cronbach's alpha for each section exceeded 0.7, with an overall reliability of 0.726. Similarly, the Cronbach's alpha for the Q23-Q25 scales also exceeded 0.7, indicating the scientific and reasonable design of the questionnaire structure and items.

3 RELATED ANALYSIS

3.1 Content Validity

Content validity, also known as face validity or logical validity, refers to whether the designed items can represent the content or theme to be measured. The correlation between each subscale and the total scale is used as an indicator to assess the content validity of the scale, examining how well a scale represents the intended theme. The results show a significant correlation between each factor and the total scale score (p-values are all less than 0.01), indicating that the scale has good internal consistency.

3.2 Construct Validity

Construct validity refers to the degree of correspondence between the measurement results and the measured value. Common methods include correlation analysis, factor analysis, and structural equation modeling. Factor analysis can extract common factors to check if the questionnaire measures the assumed structure. Before factor analysis, we conduct the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. A KMO value close to 1 indicates strong variable correlation, suitable for factor analysis; a high Bartlett's test value indicates high variable independence, also suitable for factor analysis.

KMO>0.9 is very suitable for factor analysis; 0.8<KMO<0.9 is suitable; above 0.7 is acceptable, 0.6 is poor, and below 0.5 is unsuitable. Using SPSS, the KMO coefficient is 0.746, and the P-value is 0.000, indicating the questionnaire's structure is well-designed and suitable for factor analysis.

These results indicate that the pre-survey questionnaire meets the survey's objectives.

3.3 Test of Randomness

During the survey, ensuring the randomness of sampling was crucial, and we employed a run test to assess the randomness of categorical variables. The run test evaluates the randomness of a sample based on the number of consecutive occurrences of variable values. We sorted the sample observations in ascending order and identified the median (or mean), dividing the sample into two parts: above and below the median (mean). The run test examines the randomness of the sample based on the number of runs formed by alternating values. In this survey, we conducted a run test for single-sample variable values to determine if the occurrences of a particular variable were random. For instance, in the case of gender, where males were coded as 0 and females as 1, we observed 84 occurrences of 0 and 230 occurrences of 1, resulting in a total of 119 runs (R). We used a constructed Z statistic to perform the run test.
In the Z statistic, where n0 is the number of occurrences of 0, n1 is the number of occurrences of 1, and R is the total number of runs, we calculated Z = -0.73. At a significance level of α = 0.05, the value falls between -1.96 and 1.96, indicating no sufficient reason to reject the null hypothesis. Thus, the sequence of gender data in the survey exhibits a relatively high degree of randomness.
Using SPSS software, we conducted sample randomization tests on various categorical variables in the questionnaire. The results indicate that the sequence of data for most variables does not violate randomness, suggesting that the survey data achieved a high level of randomization and was successful.

4 ANALYSIS OF CHARACTERISTICS OF USERS

4.1 Model Selection and Establishment

In data mining, k-modes is considered a method suitable for clustering analysis of categorical data sets. It extends from k-means by adapting it to handle categorical data after discretizing numerical data. The k-modes clustering method measures distances between samples using the 0-1 matching dissimilarity measure and updates cluster centers using modes. Under this distance measure, dissimilarity between a sample variable and a cluster center is computed based on the count of features where they differ (1 for different values, 0 for identical values). In k-modes, smaller distances between two sample variables indicate greater similarity.
Let $D = \{x_1, x_2, \dots, x_n\}$ be a dataset consisting of n sample variables. Each sample variable x_i has m categorical attributes, where $x_i = \{x_{i1}, x_{i2}, \dots, x_{im}\}$ composed of mmm attributes. Here, $x_{ij} \in A$, and A is the attribute set $A = \{A_{1,}A_{2,}\dots, A_m\}$. The dissimilarity between two variables x_i, x_j is measured as:

$$d(x_i, x_j) = \sum_{l=1}^{m} \delta(x_{il}, x_{jl}) \tag{2}$$

If the n variables in D are divided into k clusters, with the i-th cluster centroid denoted as $q_i, i = (1, \dots, k)$, and the distance measure from the i-th variable's data belonging to the r-th cluster is $d(x_i, q_r)$, then the objective function that defines the distances from all variables to all cluster centroids is:

$$P(W, Q) = \sum_{r}^{k} \sum_{i}^{n} w_{ir} d(x_i, q_r) \tag{3}$$

Here, $q_r = \{q_{r1}, q_{r2}, \dots, q_{rm}\}$, where q_{rh} is the mode of the h-th attribute of the r-th cluster.

$$\sum_{r=1}^{k} w_{ir} = 1, \sum_{r=1}^{k} w_{ir} \in \{0, 1\}, \ 0 < \sum_{i}^{n} w_{ir} < n, 1 \le i \le n, 1 \le r \le k \tag{4}$$

Due to the predominantly categorical nature of the collected data, we utilized the k-modes model for analysis in the following steps:
Specify the dataset D and the number of clusters k.
Arbitrarily select k sample variables as initial cluster centers, with each center representing a cluster.
Compute the distance measure $d(x_i, q_r)$ between all variables and the k initial cluster centers. Assign each variable to the closest cluster center to form new clusters.
For each attribute within each cluster, select the most frequent attribute value as the new ·
Regarding variable selection for modeling, we chose nine variables: gender, age, disposable income, platform engagement level, platform usage frequency, grass planting frequency, purchase frequency, preferred product categories, and preferred product attributes to classify user types.

4.2 Model Introduction

The random forest regression model uses the Bagging ensemble learning algorithm to create multiple samples by repeatedly sampling with replacement from the original dataset. Each sample set is used to build regression decision trees, where each tree selects feature variables as nodes and splits them based on the modeling sample data. Each split corresponds to an output value, allowing the model to classify feature variables and derive regression results. The final prediction in random forest regression is the average output of all decision trees. Like traditional linear regression models, variables are categorized into independent (feature) and dependent (target) variables, and feature selection is crucial before modeling. The process is outlined as follows:

1) Assuming there are M samples and N feature variables in the original dataset, the M samples are divided into training and testing sets in an 80:20 ratio. The training set is used to build the random forest model, while the testing set is used to evaluate the model's performance.
2) Using the Bagging ensemble learning algorithm, k iterations of random sampling with replacement are conducted on the training set, where each iteration samples approximately 2/3 of the training set data. These samples are used to form new sample sets, from which k regression decision trees are constructed. The remaining 1/3 of the training

set data, which is not sampled in each iteration, forms a set called Out-of-Bag (OOB) data. The OOB data is used for analyzing the importance of feature variables.

3) Selecting n (< N) feature variables from the total N variables to compare Root Mean Square Error (MSE) or Mean Absolute Error (MAE), dividing them into multiple units, with each unit corresponding to a fixed value. The selected n feature variables are used as the number of variables mtry randomly sampled each time a single decision tree grows.
4) The decision tree continuously splits and classifies feature variables based on sample data from the training set and the selected n feature variables, undergoing unpruned splitting growth until outputting the regression prediction result.
5) Taking the average of the output results from k decision trees as the final value for regression prediction using the random forest model.

4.3 Factor Analysis

After encoding and processing the information collected from the questionnaire, using whether to make a purchase as the dependent variable y, and gender, age, monthly disposable income, grass-planting platform, usage frequency, grass-planting format, grass-planting sharer, and grass-planting style as independent variables $x_i, i = (1,2, \ldots, 8)$, a random forest classification model is employed to compute feature importance. This is used to assess the influence of each factor on purchasing behavior.

$$y = \begin{cases} 1, & \text{purchase frequency} \neq 1 \\ 0, & \text{purchase frequency} = 1 \end{cases} \quad (5)$$

Among them, "content format" includes four formats: 'short videos', 'long videos', 'images and text', and 'live streaming'. "grass-root influencers" includes four types: 'celebrities', 'internet celebrities', 'professional bloggers', and 'amateurs'. "grass-root aesthetic" includes five styles: 'theme list-style', 'plot-style', 'unboxing-style', 'favorite items compilation-style', and 'experience review-style'.

Divide the data into training and test sets in a 70% to 30% ratio, and input the training set data into the random forest model for computation.

In terms of the Accuracy metric, factors such as usage frequency, grass-root style, and grass-root influencers have a significant impact on user purchase frequency. On the other hand, according to the Gini index, usage frequency, grass-root platform, and grass-root content style are the primary factors influencing user purchase frequency. Among these factors, usage frequency stands out as the most critical factor influencing whether users make purchasing decisions. Therefore, collectively, factors such as usage frequency, grass-root style, grass-root influencers, grass-root platform, and grass-root content style are crucial in influencing user purchasing behavior.

5 SUMMARY AND RECOMMENDATIONS

5.1 Summary

5.1.1 From the platform's perspective

Based on different content ecosystems, each platform has distinct grass-root characteristics:

1) Xiaohongshu (Little Red Book) emphasizes practicality and authenticity:

Practicality: Beauty and food content integrate product features through skill tutorials or practical user experiences, clearly showcasing user focus points.

Authenticity: Creators share post-product-experience notes from multiple dimensions, presenting product characteristics and usage experiences in a lifelike manner that attracts users.

2) Douyin (TikTok) focuses on convenience, closed-loop interaction, and precision:

Convenience: Features like live streaming and comment section links shorten the distance between users and brands, facilitating rapid conversion from interest to action, enhancing the effectiveness of grass-root recommendations.

Closed-loop interaction: Integration of public, commercial, and private domain traffic creates a closed-loop diversion enhancing the effectiveness of grass-root recommendations.

Precision: Douyin's centralized algorithm recommends content tailored to user preferences and interests, significantly increasing content consumption time and accurately meeting user needs, effectively stimulating grass-root interest.

3) Bilibili emphasizes creativity and professionalism:

Creativity: Diverse formats such as reviews, unboxing, and tutorials are presented through medium to long videos, captivating users with creative and entertaining content.

Professionalism: Gatherings of experts and diverse specialized content make Bilibili a unique hub for knowledge-based and technical content, establishing its distinctive content style.

4) Weibo focuses on longevity, practicality, and amplification:

Longevity: Multi-layered comments enhance product features and deepen user engagement, building a comprehensive scenario that sustains long-term grass-root influence.

Practicality: Shareable content featuring creators in various roles and everyday scenarios enhances practicality and penetration of grass-root content.

Amplification: Leveraging celebrity and trending topics attracts brands to promote and amplify product endorsements on Weibo, quickly expanding grass-root influence across various circles.

5.1.2. From the user's perspective

1) Xiaohongshu: Users show broad preferences but inconsistency between grass-root interest and purchasing behavior. Among young users aged 18-22 with disposable incomes of 1000-1500 RMB, there are two groups: frequent grass-root engagers who purchase occasionally. They exhibit diverse preferences across product categories and prioritize quality and price.
2) Douyin: Users generally align grass-root interest with purchasing behavior, but significant differences exist among user categories. The audience includes diverse income groups (below 1000 RMB to above 2000 RMB), with active daily users primarily interested in daily essentials. Higher-income male users prioritize daily essentials without specific product attribute preferences.
3) Bilibili: Users vary significantly in platform usage frequency, but overall, purchasing frequency is low. There are categories of users who rarely use the platform and those who log in daily, yet both groups show low purchasing behavior. Quality and price are important attributes across all user categories, focusing on practicality.
4) Weibo: Users demonstrate inconsistency between grass-root interest and purchasing frequency, with overall low platform usage. Among the two categories of female users, there are instances of alignment between usage and purchasing frequency, but discrepancies in grass-root engagement.
5) Users across platforms generally have broad preferences for product categories, particularly focusing on aesthetic appeal, with a majority falling within the 1000-1500 RMB income range.

5.2 Recommendations

5.2.1 Xiaohongshu

Xiaohongshu users have diverse preferences for products, but face challenges where grass-root interest does not always translate into purchase behavior, and where platforms for grass-root content and shopping differ. The key to addressing these issues lies in converting traffic into customers. While the platform is positioned as a sharing platform, influencers can potentially convert their followers into loyal customers.

Firstly, Xiaohongshu serves as a handy tool for users in daily life, offering solutions for various needs. To expand its market, highlighting advertisements where users can directly purchase products on the platform is essential.

Secondly, raising the bar for merchant entry and improving platform services, including pre-sales, after-sales, and user convenience, requires extensive market research to identify and address platform deficiencies.

Lastly, understanding user needs and boosting usage frequency is crucial. Adjusting the interface based on user preferences, inviting renowned brands to join the platform for increased exposure, and enhancing user engagement through tailored content and interactive activities are effective strategies.

These efforts aim to enhance Xiaohongshu's appeal and user engagement, ensuring that it meets user expectations while fostering a vibrant community of content creators and enthusiasts.

5.2.2 TikTok

TikTok users show consistent interest between grass-root content and purchases, yet there are significant differences across user categories. Male users, particularly those with higher disposable incomes, lean towards lifestyle products. TikTok's advantage lies in its convenience, with live streaming providing a direct product experience and comment links bridging the gap between users and brands. To enhance TikTok's grass-root strategy, addressing user categories is crucial.

Based on our segmentation, TikTok users are categorized into four groups. For females aged 23-25 with disposable incomes of 1000-1500 RMB, preferences include beauty, daily essentials, snacks, and clothing, focusing on product attractiveness, brand reputation, and pricing. However, their engagement in grass-root content and purchasing is relatively low. To address this, tailored pushes for beauty, daily essentials, snacks, and clothing categories can be based on user profiles and algorithmic analysis.

For males aged 23-25 with incomes above 2000 RMB, although they use the platform daily, they rarely engage in grass-root content or purchasing. There's untapped potential here due to their platform reliance. Market research is needed to explore products of interest to males, possibly including more male-oriented brands.

5.2.3 Bilibili

Bilibili users vary in how often they use the platform and generally have low purchase rates. Young males prefer educational supplies and value product reputation and pricing. Young females have a broader preference, including beauty products, daily essentials, snacks, beverages, clothing, and educational supplies, also focusing on product reputation and pricing.

Initially centered on anime and related content, Bilibili has evolved into a learning and lifestyle platform where UP creators share their favorites and Vlog records. Grass-root content is tailored to UP creator styles and segmented into different groups. Converting users into buyers effectively depends largely on managing UP creators on the platform.

Furthermore, Bilibili could strengthen partnerships with beauty and fashion brands, leveraging its professional creative style. Special incentive programs could encourage UP creators in these fields to produce high-quality content, expanding user demographics and improving grass-root categories. Attention to pricing sensitivity among all users allows collaborations with brands to offer cost-effective grass-root experiences.

5.2.4 Weibo

Weibo users exhibit inconsistent rates of interest in products they endorse and purchase, alongside generally low usage frequency. The user base can be categorized into two main groups, both consisting of females. Users aged 18-22 with disposable incomes between 1000-1500 RMB frequently use the platform and make purchases, favoring beauty and skincare products while prioritizing brand reputation and pricing. Those aged 23-25 within the same income bracket show interest in lifestyle goods, clothing, and educational supplies, but their usage and purchasing frequency are comparatively lower. Weibo should enhance its appeal and increase user engagement, particularly by highlighting niche products.

For mature female users aged 23-25, Weibo serves primarily as a hub for celebrities and their fans, necessitating diverse content offerings beyond entertainment to cater to varying user needs, including increasing exposure for niche products. Regarding male users, Weibo could expand opportunities such as celebrity live-streamed product promotions and streamline purchasing processes to improve convenience.

Improving platform functionality, introducing shopping capabilities, simplifying the endorsement-to-purchase process, and enhancing user convenience are critical steps for Weibo. Strengthening community management, particularly through topic-specific forums and groups, and fostering closer interactions between fans and influencers will amplify the influence of key opinion leaders in product endorsements.

In conclusion, each grass-root marketing platform should leverage market research to optimize their strengths and address user needs to ensure sustained growth.

COMPETING INTERESTS

The author have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] China Internet Network Information Center. The 50th Statistical Report on Internet Development in China. (2022-08-31) [2022-09-20]. Available at: http://cnnic.cn/n4/2022/0914/c88-10226.html.

[2] Clay Shirky. Cognitive Surplus. Translated by Hu Yong and Haliss. Beijing: Renmin University of China Press, 2011: 204.

[3] Du Kangyi, Zhao Hongshan. Grass-Roots Marketing of Xiaohongshu App. National Circulation Economy, 2019(22): 34.

[4] Jiang Jianguo, Chen Xiaoyu. Network "planting grass": social marketing, consumption induction and aesthetic fatigue. Learning and Practice, 2019(12): 125131.

[5] Fu Donghan, Hu Li. A brief discussion on the phenomenon and development trends of mobile Internet grass planting marketing. Communication and Copyright, 2020(08): 142-144.

[6] Wei Jiaxiao, Liang Yingtao. Research on content optimization strategy of short video platform KOL "planting grass". Audiovisual World, 2021(05): 59-61.

[7] Nie Luli. Research on the content optimization strategy of social platform KOL "planting grass". News Frontier, 2022(13): 73-74.

[8] Li Zhongmei, Huang Min. Research on countermeasures of "planting grass" content marketing in the context of new media—taking Xiaohongshu as an example. Shopping Mall Modernization, 2022(21): 13.

[9] Liu Siyu. Research on women's impulse buying intention under social marketing. Xiamen University, 2020.

[10] Wang Shixin. "Planting grass"/"pulling grass": Research on fan consumption behavior in the context of social media. Henan University, 2020.

[11] Sun Yan. Research on the "grass planting" behavior of Xiaohongshu users from the perspective of participatory culture. Dongbei University of Finance and Economics, 2022.

[12] Fang Xuelan. Research on the "grass planting" landscape of the Internet from the perspective of consumerism. Zhejiang Gongshang University, 2022.

[13] Deng Sha. Research on the impact of KOL's "grass planting" on users' purchase intention. Yantai University, 2022.

[14] Hong Yu. A brief analysis of the "grass-planting economy" in the era of self-media. Audiovisual, 2020(02): 169-170.

[15] Lei Jinghui. Research on trust construction based on "grass planting" sharing in virtual sharing communities. Shenzhen University, 2020.

[16] Li Jiawen. A brief analysis of the culture of "planting grass" in the context of the Internet - Taking Xiaohongshu as an example. Sound Screen World, 2022(21): 117-119.