Insights into the Correlation Between Digital Marketing Effectiveness and the 5A Crowd Assets Model

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Abstract. This paper examines the importance of crowd assets for the brand in the environment of changing FMCG consumer behavior and media. Based on the scientific analysis methodology for crowd assets of 5A model, this paper investigates the correlation and relevance of demographic behavior and consumer purchase from the perspective of different demographic characteristics. Based on this, methods for improving the efficiency of crowd assets operation are produced.

Keywords: Digital marketing · 5A crowd assets · e-commerce · FMCG

1 Introduction

Whether the physical world of the past or the digital world of today, marketing, as a discipline that studies the relationship between input and output of a series of complex behaviors such as human social cognition, media, and communication, always revolves around matching the supply side and the demand side. There are large number of generalisable behavioral laws in the science, which is called marketing science [1].

Marketing science, as the study of complex systems, follows the basic path of scientific research, from hypothesis formulation and testing to conclusion drawing. As a behavioral system involving consumers, companies and media, marketing is complex and full of uncertainty [2].

In the digital age, data and technology have become the engines driving the development of marketing. To properly take use of these data and technology, marketing science is needed. Marketing science is the process of developing hypotheses, measuring, validating, and applying them to chaotic and complex behavioral systems. Every marketer needs to understand it [3].

2 Digital Marketing Theory and the Landing of Contemporary e-commerce Data Platforms

2.1 Digital Marketing and Consumer Operations

"Half the money I spend on advertising is wasted. The trouble is I don't know which half", is a question posed by Werner Meck, the father of department stores, 120 years ago. It has spawned a new marketing discipline "Measurement " [4].

Over the past century, "Measurement" has become a multi-disciplinary discipline spanning marketing, mathematics, and statistics, IT and other fields, which has also become the most scientific and rational approach to creativity-led marketing. It is also the most scientific and rational part of marketing [5].

In the past decade, along with the digitalisation of marketing, measurement supported billions of RMB digital marketing ecosystem. From the perspective of advertisers, "No Measurement, No Budget" is the principle of allocating marketing budgets. Nowadays, measurement has entered a new stage of development: the era of "digital marketing measurement" [6].

What is the difference between digital marketing measurement and traditional measurement? Firstly, the data capabilities of measurement have taken a leap forward through various marketing technologies [7].

(1) The audience reached by different digital devices (PC, smartphone, smart TV…) can be identified at ID level of granularity;
(2) Behavioral data such as impressions, clicks, bounces, etc. can be recorded to evaluate marketing effectiveness;
(3) User behavior, CRM, membership, and other marketing data can be connected through a unified audience ID (one ID). So the full chain of ID-level audience journeys from awareness to conversion can be built.

Secondly, the value of measurement goes beyond traditional budget allocation management but permeates all aspects of digital marketing:

Customer Journey conversion analysis: This is the biggest breakthrough in the digital marketing era. With the conversion data chain linked by audience UNI ID, marketers can, for the first time, take use of the data at a micro level to tell how much revenue of marketing investment has brought to the business [8].

The whole chain from budget allocation to marketing execution: The digitalisation of marketing has greatly improved the efficiency of marketing operations. Measurement has penetrated the entire chain of marketing execution, from diagnosis, strategy, optimisation to effectiveness evaluation. Top digital advertisers are able to make decision based on the results of yesterday's campaigns, which significantly reducing the likelihood of making mistakes [9].

The implementation of the "How Brands Grow" growth methodology: How can marketing drive conversions? The theoretical basis for this question is the three elements mentioned in "How Brands Grow" by Byron Sharp, a North Australian professor. Target Audience (TA) + Penetration + N+ Reach, which eventually turned the growth question into a measurement question, resulting in the common N+ Reach measurement system [10].

It is clear digital marketing is an important part of in contemporary times. Amongst the many aspects, consumer operations are the foundation of digital marketing.

2.2   Crowd Assets Model from Traditional to Digital Marketing

The science behind marketing is inextricably linked to the operation of crowd assets.

The formula "AIDA": (A is Attention, which means attention is drawn; "I" refers to Interest, which refers to arousing interest; D is Desire, which stimulates desire; The

last letter A is Action, which facilitates the purchase) was one of the first widely used means of describing customer marketing patterns. It produced by sales and advertising pioneer E. St. Elmo Lewis and first applied to advertising and sales fields.

It is a simple reminder and checklist tool to help advertising practitioners design advertisements or salespeople sell their products. Like the 4Ps theory of marketing (product, price, promotion, and place), AIDA has undergone a number of revisions and expansions. Derek Rucker from the Kellogg School of Business has modified the AIDA model, shaping a new model 4A.

In 2017, Alibaba launched the Data Bank platform to operate crowed assets of brands on Taobao through a data-driven approach. The crowd model AIPL is also produced by the time. AIPL is a consumer hierarchy model based on the 4A theory and applied in conjunction with consumer e-commerce behaviors. AIPL condenses from Awareness, Interest, Purchase and Loyalty.

The AIPL model can help merchants match different strategies to meet the needs of customers at different stages through different payment tools, matching different scenarios, plus premiums and creative, respectively.

Tt is not difficult to accurately measure the purchase and loyalty of customers, as long as the transaction data is used for statistics. But it is difficult to measure awareness and interest online. However, in online e-commerce environment, it becomes possible to measure the AIPL of a user's brand across the entire chain on the Data Bank.

2.3   Upgrade of Crowd Assets Model-- 5A

Since the rapid development of short-video and live-streaming in 2020, content recommendation form of e-commerce has raised great attention in advertising industry. With the rise of TikTok short video platform, the demand for marketing science of interested e-commerce has risen. TikTok has also used the 5A model in Marketing 4.0 for reference to build its own data system for crowd assets.

The 5A model is proposed by marketing professor Philip Kotler in Marketing 4.0, corresponding to Aware, Appeal, Ask, Act, Advocate, revealing the relationship between consumers and brands. After application, what is the impact of 5A on purchasing of e-commerce? Is the model of crowd assets really make sense of e-commerce?

3   Study Design

3.1   Research Background

By the data collected based on the consumer behavior in TikTok, research could be conducted on whether 5A population has an impact on consumers' behavior.

The distribution of buyers sources in TikTok in 2022 reveals that the proportion of A3, A2 and A1 of 5A crowed assets is gradually decreasing. During the promotion period of 618 and D11, the influence of A3 population significantly increased. Thus it can be seen that A3, as the closest link to buyers, has a significant impact on consumers' purchase decisions. As shown in Fig. 1.

In addition, it can also be seen that not all consumers come from the A3 group, there are still some consumers from the A1, A2 and even O groups (non-5A groups). This
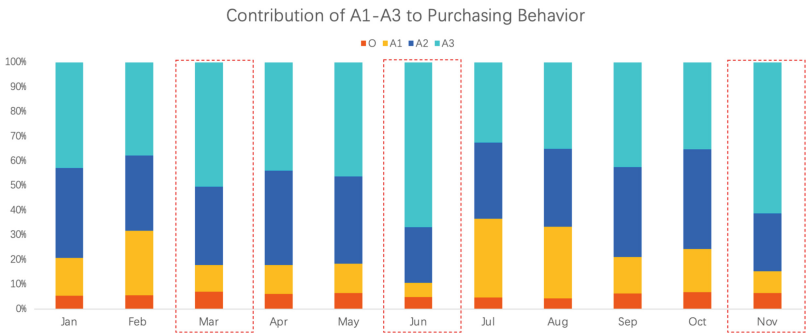
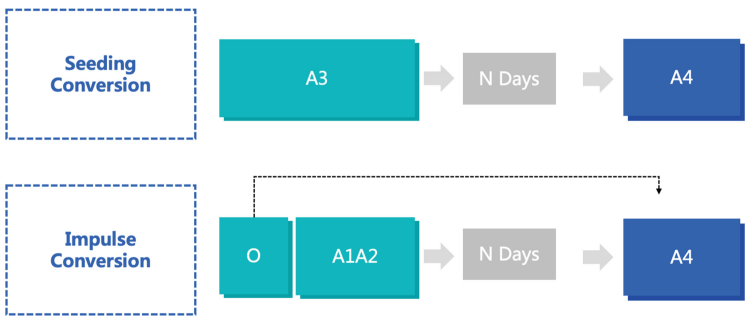**Fig. 1.** A1-A3 Facilitation diagram for purchasing behavior

Fig. 2. Planting and conversion and impulse buying charts

confirms Philip Kolter's statement that the stages in the 5A model are not strictly linear and sometimes even spiral, much like the female shopping mindset. Customer's lack of energy may often lead to skipping one of these stages.

For example, a customer may not be interested in a brand at first, but a recommendation from a friend may make him decide to buy. This means that the customer has skipped the attraction stage, and has gone straight from the understanding stage (A1\A2) to the enquiry stage (A3). On the other hand, many customers may skip the enquiry stage and impulsively buy a product based on the information they received during the understanding and attraction stages.

After sorting through the data, the consumer transformation chain can be divided into two modes: Planting & converting and Impulse buying, which can be organized as shown in the following diagram: As shown in Fig. 2.

3.2 Correlation Analysis of Seeding with A3

In order to further analyse the impact of A3, the consumer behaviour is further broken down into two levels: the first level is from understanding to interest to search, which could be called seeding path. To clarify the impact of A3 on the seeding path, this paper analyses the relationship between the A3 volume of FMCG products and the related search terms in the TikTok.
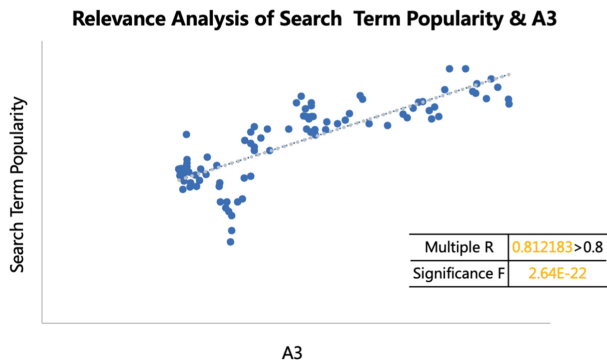
Fig. 3. Relevance Analysis of Search Term Popularity & A3

The following figure (Fig. 3) shows the relationship between A3 and related search terms for different categories/brands. Through linear regression, we found that there is a significant positive correlation between A3 population and search volume trends (Multiple R > 0.8, P value < 1%). In other words, when the A3 volume level is higher, the search popularity of that brand/category is higher.

3.3 Correlation Analysis Between A3 and GMV (Gross Merchandise Volume)

When it comes to the second stage of influence on purchase, is there any positive correlation between A3 and GMV (Gross Merchandise Volume)?

In this paper, we conduct a correlation analysis between A3 and brand GMV. Spearman's correlation coefficient is used to examine the correlation as the observation value. The correlation coefficient between A3 and GMV is about 0.54 (higher than 0.5), which can show that there is a positive correlation between A3 and GMV, but the correlation is weak. As shown in Fig. 4.

So even though A3 can influence both of seeding stage and the number of purchasers to a large extent, there is still a large uncertainty about the influence of GMV. As GMV
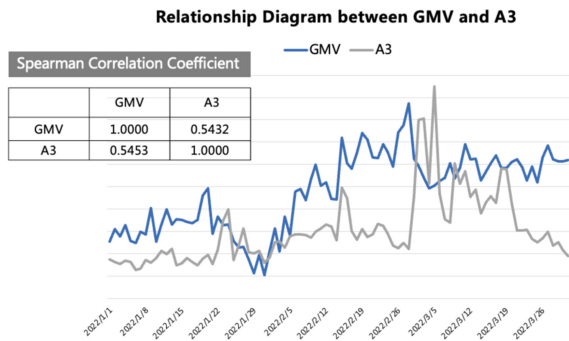

Fig. 4. A3-GMV impact seeding stage and number of purchasers comparison chart

= number of purchasers * unit price/purchaser, GMV is also greatly influenced by brand prices.

3.4 K-means Clustering Algorithm

K -means means algorithm is an iterative algorithm that K - means means algorithm has the advantages of simple principle, good clustering effect and easy It is widely used for data clustering in various industries. It divides the dataset into different and non-overlapping clusters, where each data in the dataset belongs to only one of the clusters.

Optimize the center of mass: Optimize the center of mass by iterating until the center of mass does not change, i.e., each data is assigned to the corresponding cluster without change. K-means is further decomposed in a mathematical way, specifically, there are m data points in the whole data set D. The number of clusters K is determined according to the demand, and the data set is divided into different clusters $(C_1, C_2, \ldots C_K)$, and the objective function of the algorithm is as follows:

$$J = \sum_{i=1}^{m} \sum_{k=1}^{k} \|x_i - \mu_k\|2 \tag{1}$$

where in addition μ_k is the center of mass of the x_i data, i.e., the mean vector of the cluster c_k. The expression is as follows:

$$\mu_k = \frac{1}{c_k} \sum_{i=1}^{m} x_i \tag{2}$$

K-means algorithm steps: (1) Input: input the data set $Q = \{x_1, x_2, x_3 \ldots x_i\}$ to be clustered, input the number of clusters K, and input the number of iterations N required. (2) Randomly select K points as the initial clustering center, and then calculate the distance from each data set Q to each of the K clustering centers by Eq. (1), and then compare the data with the smallest distance to the corresponding clusters, and then recalculate the position of each center by Eq. (2), and finally repeat the above steps until the center does not change and the input number of iterations is completed. The clustering analysis will stop. In this study, the K-means clustering algorithm will be used as the evaluation rule to classify the labels corresponding to the retailers into 5 categories and assign them the corresponding scores.

4 Research Conclusions and Values

To conclude, 5A has great reference value for the operation of FMCG brands in TikTok. From the seeding stage, it can significantly influence the brand's popularity, while the model of 5A crowd assets can also influence the composition of the final transaction crowd. But brand sales and market share are seriously affected by purchaser unit price. In order to increase market share, it is necessary to enhance the coverage of 5A crowd assets with the help of crowd operations, and promote brand image to increase premium ability at the same time.

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