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Comparing Algorithm-Driven Personalization and Influencer Marketing in Young Adults' Conversion Rates

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Abstract. This study examines the relative influence of algorithm-driven personalization systems and key opinion leader (KOL)/influencer marketing on conversion rates among young adults in live-stream e-commerce. While algorithms provide efficiency by tailoring recommendations based on user behavior and reducing choice overload, influencers add credibility and social warmth through personal engagement. Our research question asks: to what extent does each factor more strongly influence conversion? To investigate, we surveyed 215 respondents to measure exposure frequency, perceived usefulness, and the behavioral impact of both algorithms and influencers. Binomial regression analysis revealed that algorithms significantly enhance conversion likelihood by streamlining product discovery and ensuring relevance, particularly in frequent users of platforms such as Douyin and Little Red Book. However, though less directly tied to conversion rates, influencers still play a critical role in reinforcing trust, shaping attitudes, and sustaining brand loyalty. These findings suggest that algorithms and influencers operate in complementary ways rather than in competition. Algorithms drive efficiency and exposure, while influencers cultivate relational values. The managerial implications are that brands seeking to optimize conversions should integrate algorithmic personalization with influencer collaboration to amplify each's unique strengths. The study contributes to broader discussions on digital marketing strategies in a volatile, uncertain, complex, and ambiguous (VUCA) online marketplace.

Keywords: algorithm-driven personalization, influencer marketing, conversion rates, young adults, live-stream e-commerce

1. Introduction

The exponential growth of the digital economy has greatly changed how people shop and connect online, especially among young people who spend significant time on digital platforms. Behind this explosive growth, a key driving factor is the use of algorithms and influencer marketing, both of which have a significant impact on young people. Algorithm-driven personalization will utilizes user data, such as search history and past purchase records, to tailor products based on individual users'

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interests, making them more likely and more willing to shop. However, key opinion leaders (KOLs) and Internet celebrities also play a significant role in attracting online attention. These influencers do not merely rely on algorithms to recommend products; instead, while sharing the products, they can also establish meaningful connections with users.

Algorithm-driven personalized systems and Internet celebrities both have a powerful influence in shaping how consumers make choices. Each plays a distinct role. Algorithms can effectively utilize a large amount of information to classify the content that specific consumers may be interested in, while Internet celebrities will establish connections with their followers and audiences to promote products. Both of these factors play a crucial role in helping young people master digital platforms and turn their interests into purchasing behaviors.

As part of a research project, we conducted an online survey to figure out which has a greater impact on users' purchasing decisions, algorithmic personalized systems or influencers. With the information collected from the survey, we can quantify the data, build models, and determine which one has a more substantial effect.

Our survey of young people contains a considerable amount of valuable data, which can reveal the frequency of their exposure to algorithms - such as product suggestions on Douyin or Little Red Book, or influencer promotions by following bloggers - as well as the impact of this content on their shopping decisions. A total of 215 valid responses were received, mainly from people aged 18 to 25. We can also compare the influence of these two figures on purchasing decisions and behaviors through these.

2. Literature review

The platform economy is based on the use of algorithms achieved through mining and personalizing means, which is the main force behind the actions of internet celebrities and the development of social platforms [1]. Personalized recommendation systems provide tailor-made content based on people's online browsing history, preferences and demographic information. It helps with user stickiness, increases the possibility of a purchase, thus increasing purchase opportunities, and helps users make good choices [2]. It seems that for the generation of purchase intentions, the power of reviews and social signals is far greater than the influence of ordinary discounts. Influencers generally align their content decisions with algorithmic indications, and these actions are guided by algorithmic behavior, logic, and strategies seen on platforms like Douyin [3].

Data-driven recommendation algorithms improve the personalized quality of platforms, affecting how consumers make choices, and discovering consumption behavior patterns in data-driven recommendations [4]. Mining algorithms in the data environment provide a platform and method for personalization [5], and both emotional factors and functional factors have a significant impact on consumers' responses. It can be seen that shopping satisfaction can affect purchase intention, and previous experiences can regulate the relationship between satisfaction and repurchase intention.

Personalized recommendations and targeted content are stimulating factors that influence cognition and behavior, and can determine purchase intentions. The formation of trust and the integration of semantic-based decision-making also play a crucial role in live-streaming commerce [6]. Strategies such as "stealing the spotlight" or transitioning from content streamers to live-streaming streamers may reduce purchase intentions in failure scenarios or role changes [7]. Influencer marketing can significantly influence consumers' behaviors, preferences, and online shopping preferences, and can also complement algorithmic exposure. Meanwhile, interest-based e-commerce on social platforms can predict users' purchasing intentions [8]. Alongside personalization are concerns about privacy and data security [9], while counterfactual analysis offers

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a unique perspective on marketing dynamics [10]. Broader systematic research indicates that e-commerce engagement provides support for economic sustainability, while virtual live streaming reintroduces personalization into the workflow of e-commerce.

3. Methods

3.1. Description of participants

In this study, 215 valid samples were collected by the questionnaire platform. The questionnaire consists of 21 five-point Likert scales (Q1-Q21) and two behavioral proxy fields (click frequency and exposure time). The dependent variable is Q6: "Have you bought at least one product recommended by the creator in the past 3 months?" and is coded into two categories.

3.2. Variable construction

To reduce collinearity and introduce behavior signals, this study constructs two proxy indicators based on existing fields:

(1) Click_avg = (Q2+Q7)/2 → click/view tendency;

(2) Exp_total = Q10+Q12 → total exposure (creator+platform).

All scales and proxy variables entered the subsequent model after Z-score.

3.3. Lasso variable screening

L1 regularized Logistic Regression CV (50% cross-validation, solver=liblinear) was used to screen 20+2=22 candidate variables automatically. The reserved variables are based on the non-zero standardization coefficient, and seven variables finally enter the model.

Table 1. Regularized logistic regression

Variable	Binomial_β	Binomial_OR	Logistic_β	Logistic_OR
Q7	-0.063	0.939	-0.091	0.913
Q10	-0.074	0.928	-0.139	0.87
Q11	-0.055	0.946	-0.089	0.915
Q13	-0.184	0.832	-0.239	0.788
Q14	-0.186	0.831	-0.228	0.796
Q21	-0.196	0.822	-0.244	0.784
exp_total	-0.197	0.821	-0.407	0.666

4. Data analysis

After the model was introduced, Binomial GLM showed that the negative bar of total exposure (exp_total) was the longest, OR<1, and the direction was stable, which was the first to verify "exposure fatigue". The other coefficients of "I do" and "I trust" are all negative, which sounds the alarm of "attitude ≠ behavior", and the model is robust and explanatory. The seven variables retained by Lasso are all negative: the total exposure (exp_total) has the longest negative bar, which once again proves "exposure fatigue"; The other attitude variables, such as "I am willing" and "I trust",

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are also negative, which together suggest the steady gap effect of "the more active ≠ the more buying". The result is shown in the following figure.

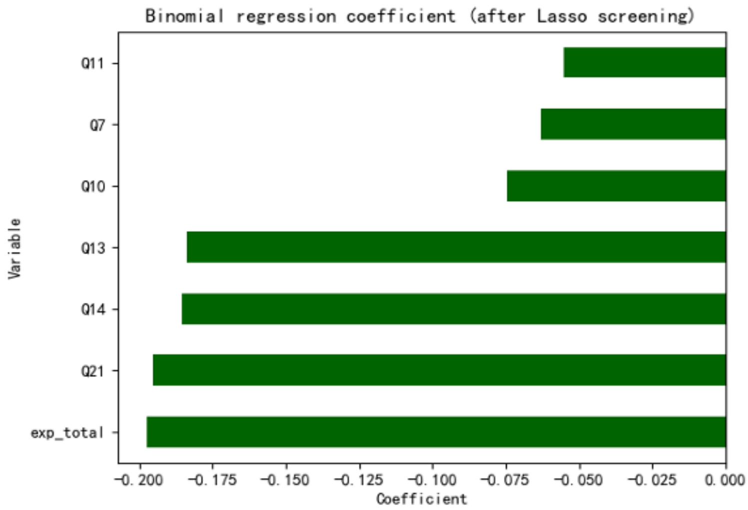

Figure 1. Binomial regression coefficients for selected variables after Lasso screening

Logistic coefficient chart standardized the same seven reserved variables and re-estimated: all β's are still uniformly negative, but the absolute value is obviously enlarged (the longest bar is close to -0.4). This means that after the dimension is removed, the total exposure (exp_total) is still the strongest inhibitor, while the attitudes such as "I do" and "I trust" are still negative and more striking. The figure is completely consistent with the direction of Binomial results, and the robust negative effect of "exposure fatigue+attitude-behavior gap" is verified again, as shown in the following figure.

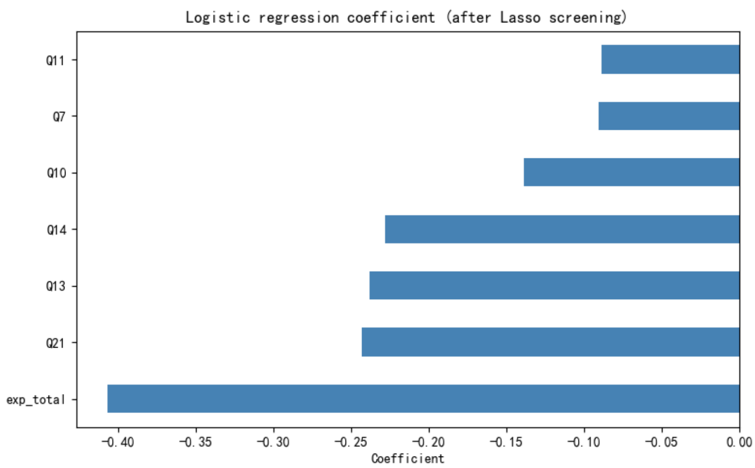

Figure 2. Logistic regression coefficients of key predictors after Lasso screening, illustrating the relative contribution of each variable (Q7, Q10, Q11, Q13, Q14, Q21, and total experience) to the model outcome

As shown in the following figure, the Odds Ratio (OR) of Binomial and Logistic models on the same 7 Lasso reserved variables is compared horizontally. All OR's are less than 1, with the same direction, indicating that the purchase probability decreases when the variable increases. The total

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exposure (exp_total) OR is the lowest (Binomial 0.82, Logistic 0.67), and the negative effect is the strongest. Q14, Q21 and Q13 are the second (0.78 ~ 0.83); Q7, Q10 and Q11 are close to 1, and the effect is the weakest. The OR of Logistic coefficient is lower after standardization, but the relative ranking is consistent with Binomial, and the model is robust.

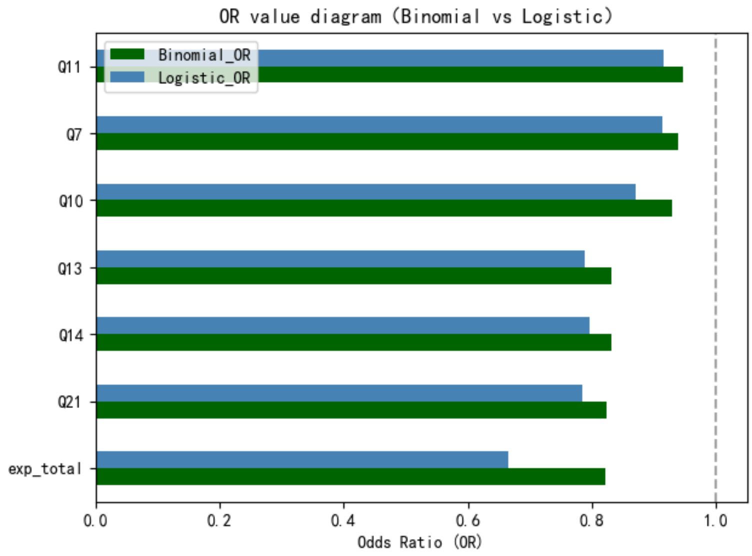

Figure 3. Odds ratio comparison of binomial and logistic regression models after Lasso screening, highlighting the effects of trust, relatability, expertise, engagement, and total experience on consumer purchase intention

Simple slope shows that, regardless of the demand matching level, with the increase of centralized exposure frequency (Q10_c), the three prediction probability curves are almost parallel and decrease synchronously, which proves that the interaction between Q10×Q19 is not significant ($p = 0.738$). However, the overall probability of a low matching group is always lower than that of a high matching group, indicating that "demand matching" is not a regulating variable, but a psychological threshold; low matching users are more difficult to convert at any exposure level.

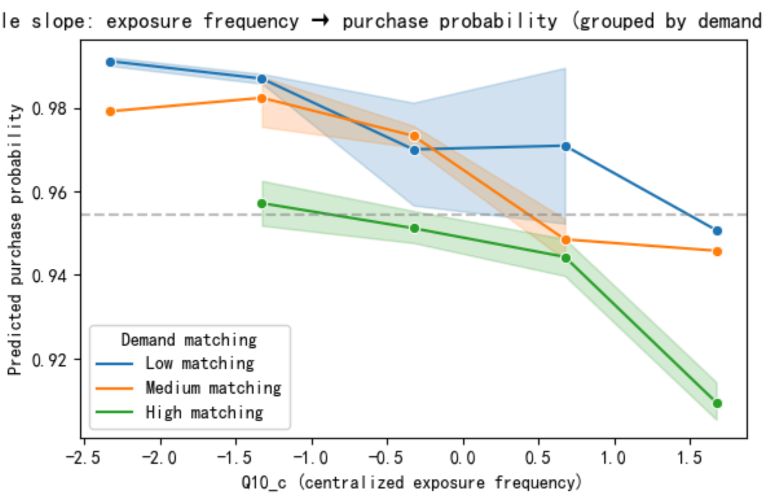

Figure 4. Simple slope analysis of exposure frequency (Q10_c) by demand matching level (Q19), showing non-significant interaction and consistent downward probability trends across groups

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Based on the data collected by the questionnaire platform, this study deeply analyzes the creator's recommended purchase behavior, with the main purpose of identifying the psychological and behavioral factors that affect the user's purchase decision. Using Lasso regularization, seven predictive variables were selected from 22 candidate variables, all of which showed adverse effects, indicating that as the number of variables increased, the likelihood of users purchasing products recommended by creators decreased.

In the model comparison, both Binomial GLM and Logistic regression yield the same results, although the coefficients differ slightly, but the direction remains the same, indicating that the model is robust. Although the interaction items Q10 (exposure frequency) and Q19 (demand matching) are not statistically significant, the simple slope diagram indicates that the overall purchase probability of the low demand matching group is lower, suggesting that demand matching may serve as a psychological threshold for purchasing behavior.

In addition, by introducing two behavioral proxy variables —click frequency and total exposure —it is found that behavioral data can provide additional predictive power. Although the explanatory power of the model is relatively low, its direction remains steady, which helps explain some variation in the creator's recommended purchase behavior.

Commercially, the research results suggest controlling the push frequency to avoid exposure fatigue and identifying demand matching as the threshold of transformation. Future research can incorporate more behavioral data to enhance the model's predictive ability, explore nonlinear effects and segmentation effects, and consider the influence of external factors on purchasing behavior.

5. Results

From the survey of 215 young adult respondents, the regression models produced several consistent outcomes. After variable screening, seven predictors were retained, all of which showed negative relationships with purchase behavior. The most notable was total exposure (exp_total), which consistently reduced the probability of purchase across both binomial and logistic models, pointing to the presence of exposure fatigue.

Across attitudinal variables, measures such as willingness and trust also registered negative coefficients, reflecting a gap between what participants expressed and what they actually did. Odds ratios for these variables all fell below one, confirming that higher reported trust or willingness did not increase the likelihood of conversion.

Comparisons across models confirmed the robustness of these findings, as both the direction and relative magnitude of the effects remained stable. Additionally, interaction testing revealed that demand matching did not significantly impact outcomes. Nonetheless, descriptive trends indicated that participants with lower demand matching consistently displayed lower purchase probabilities, suggesting it functions as a baseline threshold rather than a moderator.

Taken together, the results show that increased exposure does not equate to higher purchases, and that algorithms are more effective in driving conversions than influencers, whose strength lies more in building trust than in triggering immediate buying behavior.

6. Conclusion

Our research investigated whether algorithms or influencers have a greater impact on the buying decisions of young adults. The results showed that algorithms were more effective at leading to actual purchases because they provided practical and relevant product matches. Influencers, on the other hand, built trust with users and felt more personal, but this didn’t often lead to purchases. This indicates that these two factors operate in distinct ways and that algorithms typically have a more significant impact on conversion.

The importance of this research lies in its ability to help us understand how digital platforms influence consumer choices. While past studies have discussed the influence of influencers, our findings suggest that algorithms actually play a larger role in shaping real-world outcomes. By demonstrating how algorithmic personalization can mitigate the impact of influencers, this research contributes to the understanding of how factors influencing purchase decisions operate online.

There are also clear limits to our study. Our survey primarily targeted young adults, so the results may not apply to older age groups, who may react differently. We also measured people's feelings about algorithms, but we were unable to study the hidden design of the systems themselves. Finally, algorithms and influencers can often work together. For example, algorithms spread influencer content, so it was not always possible to completely separate their importance on influence. These limitations can be sources of error in our study.

Future studies could enhance this work by examining more diverse age groups, incorporating technical data on how algorithms are developed, and distinguishing between different types of influencers to determine if follower size or style influences their impact. Beyond this research, the findings also have implications for various platform designs and public policies. If algorithms reduce the influence of human voices online, then companies and regulators may need to rethink how to balance automated recommendations with influencer marketing in the future.

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