

The Impact of Personalized Recommendation Algorithms on Consumers' Purchasing Decisions

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Abstract. Against the backdrop of ubiquitous big data and algorithmic mediation, recommender systems have become the dominant channel through which consumers discover products and form preferences. As artificial intelligence advances and platform economies expand, algorithmic recommendations now permeate every stage of digital consumption, reconfiguring the interactions among users, goods, and marketplaces. On e-commerce platforms in particular, personalized recommender systems serve not only as engines of conversion but also as subtle architects of decision paths and preference structures. The present study combines survey evidence with click-stream data to examine the causal impact of these systems on purchase behavior. Results indicate that algorithmic recommendations significantly increase click-through and purchase intentions, yet tension persists between accuracy and diversity. Users exhibit a calculated trade-off—surrendering a degree of control in exchange for cognitive efficiency. Drawing on questionnaire responses and secondary click data from Taobao, the paper underscores the need for governance frameworks that balance commercial effectiveness with user autonomy.

Keywords: E-commerce platforms, big data, personalized algorithms, consumer psychology.

1. Introduction

Algorithmic personalization now mediates nearly every facet of digital life. Short-video apps, navigation services, and online marketplaces all tailor content to inferred individual tastes, thereby shaping everyday decisions. In China, leading shopping applications such as Taobao, Douyin, and Xiaohongshu rely heavily on personalized recommendations to target users with precision. As consumption migrates online and the digital economy deepens, platforms increasingly delegate traffic allocation to algorithms that predict, nudge, and convert. Consequently, algorithmic systems have evolved from back-end operational tools to foregrounded determinants of consumer preference and intent [1]. Existing scholarship has dissected the technical anatomy of recommender systems—collaborative filtering, matrix factorization, and deep learning variants—and documented their performance across information retrieval, social media, and location-based services. A smaller but growing literature investigates the psychological mechanisms through which algorithms alter perception and behavioral intention. Yet, within the high-involvement context of online shopping, systematic empirical evidence on how algorithmic recommendations influence the entire decision journey—from initial awareness to final purchase—remains scarce. Prior work has centered on library retrieval, travel, and food delivery; the shopping domain itself has received comparatively little attention [2,3].

This study asks: How, and to what extent, do personalized recommendation algorithms affect consumers' shopping experience and purchase decisions? To answer the question, it combine survey responses with actual sales data from multiple platforms and subject them to regression analysis. The findings inform platform operators seeking to refine marketing strategies and calibrate data flows, while also shedding light on user attitudes toward algorithmic curation.

It proceed in three steps. First, a questionnaire elicits shopping preferences and perceived responsiveness to algorithmic recommendations, allowing us to link subjective dispositions to objective algorithmic outcomes. Second, leveraging Taobao's ad-click logs and user-level spending tiers, it apply chi-square tests to establish behavioral correlations between algorithmic exposure and purchase acts. Finally, it integrate attitudinal and behavioral datasets to test the central proposition

that personalized recommendations shape purchase decisions via a dual mechanism of cognitive priming and behavioral channeling.

2. Survey Evidence and Psychological Analysis

Personalized recommendation, as a technology that infers potential preferences and matches content by observing user behavior, aims to serve human subjects with emotions and perceptions. Therefore, it needs to be comprehensively examined from the perspectives of social sciences and engineering. Based on this concept, it conducted a consumer experience questionnaire survey targeting active e-commerce users under the age of 45. Out of the 120 questionnaires distributed, a total of 108 valid responses were collected, and the final analysis was based on a balanced subset with a scale of 100.

The survey results show that in terms of platform penetration, Taobao/Tmall leads with 78% coverage, followed by JD (65%), Pinduoduo (52%), Tiktok/Kwai (48%), Xiaohongshu (36%) and other platforms (12%). On the perception level of recommended content, 82% of respondents often pay attention to platform recommendations, 15% occasionally pay attention, and only 3% never pay attention. Regarding recommendation relevance, 18% consider it "very relevant", 55% consider it "basically relevant", 20% have a neutral attitude, and 7% consider the content irrelevant.

The recommendation mechanism significantly affects user behavior: 63% of users indicate that they always or frequently click on recommended products, 30% occasionally click, and only 7% rarely or never click. In addition, 58% of users have purchased unplanned products due to recommendations, while 42% reported rarely or never engaging in such behavior. Overall satisfaction is high, with 68% of users expressing satisfaction or very satisfaction, 25% having a neutral attitude, and 7% being dissatisfied. User complaints mainly focus on repetitive content (45%), privacy concerns (32%), and insufficient recommendation accuracy (23%).

2.1. Interpretation

Incumbent platforms (Taobao, Tmall, JD) dominate user choice, while Pinduoduo captures the value segment and short-video marketplaces (Douyin, Xiaohongshu) gain traction via immersive content. Overall, users view personalized recommendations favorably: more than 80 % are consciously aware of the algorithm, 63 % routinely click "guess you like" modules, and 58 % admit to impulse purchases triggered by the feed. Figure 1 and Figure 2 attest to the algorithm's deep penetration and its capacity to elicit unplanned spending.

Yet accuracy remains imperfect. While 73 % judge recommendations "basically" aligned with their needs, 45 % complain of redundancy—evidence of mechanical over-fitting and limited long-tail discovery. Privacy unease coexists with functional satisfaction; users appear willing to trade data for convenience, revealing a calculated dependency rather than unqualified enthusiasm. Short-video platforms engender higher reliance, plausibly because immersive live-streaming and influencer endorsements prime viewers for subsequent algorithmic retargeting [4].

2.2. Psychological Mechanisms

Why do shoppers delegate decisions to algorithms? Three interlocking mechanisms emerge. Choice overload. The abundance of online options exacerbates decision fatigue. Under time pressure, consumers adopt a "recommendation-as-heuristic" mindset, accelerating choice while curtailing deliberation [5,6]. This efficiency gain fosters habitual reliance on algorithmic cues.

Identity reinforcement. Recommendations that consistently mirror one's style yield a "the algorithm understands me" epiphany, generating positive affect and a sense of ontological security. The feed becomes a mirror reflecting and amplifying the consumer's self-concept. Tags such as "women aged 20–25 also bought" or "plus-size favorites" situate the user within a reference group. Some shoppers deliberately train the algorithm to crystallize a desired social identity, thereby transforming the recommender into an instrument of self-presentation.

2.3. Extensions

Current systems still suffer from mechanical narrowness and cold-start problems. New products or users with sparse histories risk invisibility, and homogeneity in the feed reinforces filter bubbles. These frictions invite technical and policy remedies.

3. Data Processing and Analysis

3.1. Data and Method

The dataset was retrieved from Kaggle, where it had been compiled by Pavan Sanagapat under the title “Ad Display/Click Data on Taobao.com”; the primary source is Alibaba’s Alimama repository.

All analyses in this study follow the standard procedure of a chi-square test of independence, a non-parametric technique for assessing associations between categorical variables [7]. Contingency tables were constructed from the Kaggle sample, and the chi-square statistic was computed in Python using the conventional. The chi-square statistic is computed in Python as

$$\chi^2 = \sum_{i=1}^n \frac{(K_i - E_i)^2}{E_i} \quad (1)$$

In this formula, K denotes the observed frequency, E the expected frequency, and X the chi-square statistic. The p -value is the right-tail probability of the chi-square distribution: $p = P(\chi^2 > X_k^2)$, where X_k^2 denotes the observed chi-square statistic and the reference distribution is χ^2 with df degrees of freedom. Degrees of freedom are calculated as $df = (r - 1)(c - 1)$, with r equal to the number of rows and c equal to the number of columns in the contingency table. If $p < 0.05$, the null hypothesis is rejected, indicating a significant association between the two variables; if $p \geq 0.05$, the null hypothesis is not rejected, implying no statistically significant association [8].

Hypotheses: H_0 (null): Shopping level is independent of click-through behavior.

H_1 (alternative): Shopping level is associated with click-through behavior.

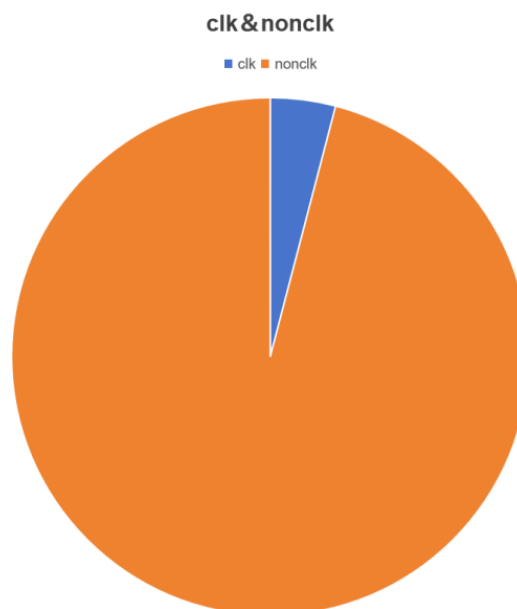


Fig. 1 Clk and nonclk (Picture credit: Original)

3.2. Descriptive Insights

Essential descriptive statistics are presented through a set of visualizations that summarize the raw data and highlight usable patterns. These graphics serve as the empirical foundation for subsequent exploratory analyses and modeling [9].

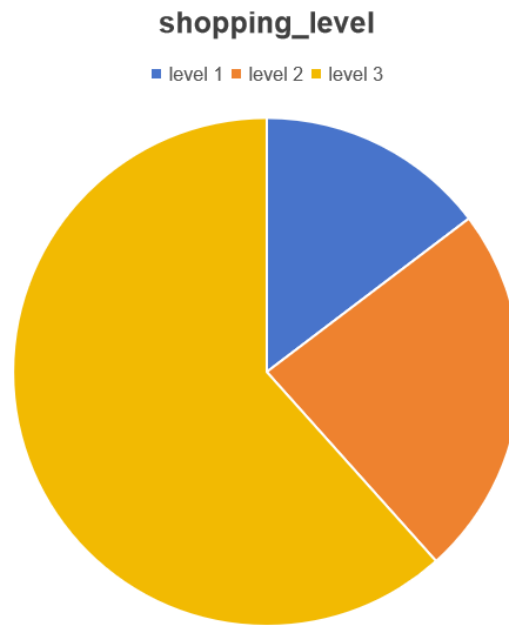


Fig. 2 Shopping level (Picture credit: Original)

Figure 2 shows the distribution of shopping levels: level-1 (low) 14.68 %, level-2 23.69 %, level-3 (high) 61.63 %—indicative of a relatively affluent sample.

Table 1. Contingency table

shopping level	clk	nonclk	Total
1	5	500	505
2	15	800	815
3	120	2000	2200
Total	140	3300	3440

Note: Owing to computational constraints and because the objective is merely to identify broad trends, a representative subset of the data—exhibiting high internal consistency—was analysed.

Table 1 shows the contingency table for user click behavior across shopping levels. The click-through rate (CTR) increases with shopping level, from ~1% at level 1 to ~5.5% at level 3, indicating a positive correlation between shopping activity and engagement. Level 3 contributes the most to both clicks and total users.

The component contributions to the chi-square statistic sum to $\chi^2 \approx 11.76 + 0.50 + 9.94 + 0.42 + 13.15 + 0.56 = 36.33$. With degrees of freedom $df = (r - 1)(c - 1) = (3 - 1)(2 - 1) = 2$, the critical values are $\chi^2(2, 0.05) = 5.991$ and $\chi^2(2, 0.001) = 13.816$. Since the observed $\chi^2 = 36.33$ far exceeds 13.816, the null hypothesis H_0 is rejected at $p < 0.001$. Consequently, shopping level and click-through behaviour are significantly associated [10].

4. Conclusion

Integrating survey and behavioral evidence, this study demonstrates that personalized recommendation algorithms materially influence purchase decisions. Survey data show that 63 % of respondents habitually click algorithmic suggestions and 58 % buy items they had not planned to purchase, corroborating the notion of a “decision shortcut.” Behavioral data reveal that high-spending users click at 5.66 %, nearly six times the rate of low-spending users (0.99 %). Yet 45 % complain of repetitive content, confirming a tension between precision and diversity. Users willingly surrender privacy for efficiency, exemplifying a broader societal calculus in which time anxiety overrides information sovereignty.

Policy implications are clear. Platforms should augment transparency—e.g., “why am I seeing this?” labels—and grant granular control, such as one-click hiding and diversity sliders. Users, for

their part, must cultivate algorithmic literacy, offering corrective feedback to mitigate over-dependence. Ultimately, sustainable governance demands a tripartite compact among platforms, regulators, and consumers to balance efficiency with autonomy, precision with pluralism.

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