

The Impact of AI-Driven Personalized Recommendation on College Students' Purchase Decisions on Small E-Commerce Platforms

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Abstract

This study investigates how AI-driven personalized recommendations influence college students' purchase decisions on small e-commerce platforms. As even smaller retailers increasingly adopt affordable AI tools and SaaS-based recommender solutions, it becomes crucial to understand whether and how personalization works for young consumers beyond big platforms. We adopt a 2×2 between-subjects experiment (explanation provided vs. not provided; short vs. long recommendation list) combined with a structured survey. Using real data (N = 391), we find that adding an explanatory rationale to recommendations does not significantly change subjective evaluations or purchase intention, whereas shorter lists (3–4 items) outperform longer lists (10–12 items) on purchase intention. Mediation analyses reveal that perceived usefulness and enjoyment are significant predictors of purchase intention; however, the paths related to “explanation usefulness/enjoyment” are not significant, indicating that the overall mediation does not hold. Additionally, moderation tests demonstrate that trust and privacy concerns do not significantly influence the effect of explanation on purchase intention. The results suggest that, for small platforms targeting college students, streamlined presentation matters more than adding generic justifications; strengthening actual usefulness and enjoyment is key to improving responses. We discuss practical implications for balancing personalization with user control and transparency.

Keywords

Personalized Recommendation; Artificial Intelligence; College Students; Small E-commerce Platforms; Purchase Decision-Making.

1. Introduction

AI-based personalization has become a core capability in digital commerce. Algorithms analyze user behavior and context to deliver relevant product suggestions, reducing information overload and potentially improving conversion. While large platforms have long reported gains from personalization, small e-commerce platforms-e.g., niche campus marketplaces or localized apps-are now able to deploy similar tools via cloud and SaaS. For college students, who are digitally native and highly sensitive to online cues, personalized feeds can shape attention and sometimes trigger impulsive choices. Yet, compared with research on major platforms, evidence from small-platform contexts remains limited. This study focuses on that gap and asks: Which presentation choices (e.g., whether to show an explanation; how long the list should be) meaningfully influence college students' decisions? Through which psychological routes might these effects occur, and under what conditions do they change?

2. Literature Review

A growing body of studies shows that AI-driven personalization significantly increases purchase intention and conversion, with stronger effects among Gen-Z/college users [1-5], and similar patterns for millennials [6]. Technically, ML-based intelligent classification and personalized recommendation enhance matching accuracy and search efficiency, thus reducing users' choice costs [7]. Managerially, AI-powered SEO and digital marketing complement recommender systems by boosting traffic and reach, strengthening conversion performance [8]. Moreover, personalized marketing and communication elevate experiential value and relationship quality, thereby supporting the recommendation-trust-purchase intention chain [9].

Across contexts, short-video social commerce (e.g., TikTok/Douyin) highlights entertainment, social proof, and creator influence in shaping young users' decisions [2,4-5], while Southeast-Asian cross-border platforms (e.g., Shopee/Lazada) reveal heterogeneous effect sizes and determinants due to cultural and platform-design differences [3]. At the same time, recommender systems can trigger impulsive buying, calling for a balance between conversion gains and consumer protection [10].

Overall, prior evidence concentrates on large or short-video social-commerce platforms [2,4-5]. In contrast, small e-commerce platforms remain under-examined regarding presentation choices (e.g., explanation cues, list length) and psychological mechanisms among Gen-Z/college users. Addressing this gap, we focus on the small-platform setting and use social-commerce findings as benchmarks to examine how explanation and list length affect purchase intention and how experiential variables (e.g., perceived usefulness, enjoyment) operate in the process [1-5,7,9-10].

3. Methodology

3.1. Design

We implemented a 2×2 between-subjects experiment:

- Explanation of the recommendation: provided vs. not provided
- List length: short (3–4 items) vs. long (10–12 items)

Participants first read a brief scenario describing the recommendation block (e.g., “each item is shown with a short reason why it is recommended” vs. “items are shown only by name and image without any rationale”). They then completed the measures. All non-manipulated content was held constant to ensure internal validity.

3.2. Measures

This study adopts two-factor 2×2 experiments: recommended explanation (0 = no explanation; 1 = with explanation) and recommended list length (0 = long list, 10–12 items; 1 = short list, 3–4 items). The dependent variable is the purchase intention (PI), which depicts the subject's purchase tendency and motivation for the recommended product; the two intermediates are perceived usefulness (PU) and pleasure (ENJ), respectively reflecting whether the recommendation improves the search/matching efficiency and the positive experience of browsing; the two adjustments are trust and privacy concerns, which are used to test the solution. Whether the information is more effective under different levels of trust/privacy; control variables include selection overload and e-commerce experience/product involvement to exclude the interference of “how many options/familiarity” with the results. All scales are 5-point Likert (1 = very disagree, 5 = very agree). The entries come from pre-tests and existing literature, and the internal consistency (Cronbach's α) is >0.80 . As shown in Table 1, we have

listed the type, name and operational definition of each variable so that readers can clearly grasp the subsequent model setting and test path.

Table 1. All variables adopt the 5-point Likert scale (1= strongly disagree, 5= strongly agree), and the scale items are adapted from the preliminary test and literature, and the internal reliability (Cronbach's α) of the scale is > 0.80.

The system of variables in this study is as follows:

Type	Name of variable	Description
Independent variable	Recommended explanation (explanation/no explanation)	The two control variables constitute a 2×2 design
Independent variable	Number of recommendations (short list/long list)	The two control variables constitute a 2×2 design
Dependent variable	Purchase Intention	Subjects' purchase likelihood and motivation for the recommended goods
Mediating variable	Perceived Usefulness	Is the recommendation more efficient/enjoyable
Mediating variable	Enjoyment	Is the recommendation more efficient/enjoyable
Moderating variable	Trust	Whether users trust recommendations and worry about data breaches
Moderating variable	Privacy Concern	Whether users trust recommendations and worry about data breaches
Other Controls	Overload	Control the burden and user background when users have too many options
Other Controls	E-commerce experience/product involvement	Control the burden and user background when users have too many options

Table 1 clarifies the modelling options of this article: the explanation/list length is experimental manipulation, and PI is the result variable; PU and ENJ are used to test the indirect path of "presenting strategy → experience improvement → purchase"; trust and privacy concerns are used to test the boundary conditions of "whether the interpretation is more effective in different situations"; select overload And experience/involved into each regression or variance analysis model as statistical control. Accordingly, Section 4.1 reports the two-factor main effects and interaction terms (and the number of effects), Section 4.2 gives the mediation test of PU/ENJ, and Section 4.3 tests the regulatory role of trust/privacy concerns. The variable framework corresponds to the subsequent model settings one by one, ensuring that the result interpretation is traceable and reproducible.

3.3. Sample and Procedure

Chinese college students were recruited by convenience sampling, and the questionnaire was released through multiple channels. A total of 391 valid samples were collected, covering four experimental conditions (group size ≥ 70). Before filling in all questionnaires, subjects were required to read the corresponding recommended situation setting, and then complete the items of each perception dimension, manipulation test, attention test and basic information.

In the data collection phase:

- Eliminate those who fail the attention or manipulation test.
- Keep records of completed and logically consistent questionnaires.
- Information in the experimental group is automatically classified according to the situational text or recorded by the system.

4. Results

In general, whether there are reasons for recommendation has a limited impact on subjects' subjective evaluation, while the length of the recommendation list has a certain impact on some outcome indicators. In terms of purchase intention, situations with a shorter list of recommendations (3-4) are significantly better than those with a longer list (10-12). There is no significant interaction between the two factors. In the following, the results will be specified and reasoned with assumptions.

Table 2. Summarizes the mean and standard deviation of the main dependent variables in different experimental situations.

Construct	With explanation - Short list (M $\pm$ SD)	With explanation - Long list (M $\pm$ SD)	No explanation - Short list (M $\pm$ SD)	No explanation - Long list (M $\pm$ SD)
Purchase Intention	3.54 $\pm$ 0.99	3.31 $\pm$ 1.02	3.38 $\pm$ 1.06	3.20 $\pm$ 1.06
Perceived Usefulness	3.54 $\pm$ 0.90	3.47 $\pm$ 0.96	3.48 $\pm$ 1.01	3.30 $\pm$ 1.01
Enjoyment	3.38 $\pm$ 1.14	3.32 $\pm$ 1.01	3.42 $\pm$ 0.98	3.31 $\pm$ 0.97
Trust	2.70 $\pm$ 1.17	2.79 $\pm$ 1.01	2.83 $\pm$ 1.02	2.73 $\pm$ 1.09
Privacy Concern	4.04 $\pm$ 0.90	3.76 $\pm$ 0.93	3.77 $\pm$ 0.95	3.70 $\pm$ 1.03
Overload	3.58 $\pm$ 0.94	3.57 $\pm$ 0.83	3.43 $\pm$ 0.98	3.60 $\pm$ 0.83

As shown in Table 2, the sample sizes of the four experimental groups are: with explanation-short list n=94, with explanation-long list n=131, no explanation-short list n=88, no

explanation-long list $n=78$ (total $N=391$). From the perspective of the mean value model, the short list is generally higher than the long list in terms of purchase intention (for example, 3.54/3.38 to 3.31/3.20), corresponding to the intuitive picture of "reducing the amount of information $\rightarrow$ easier to make decisions"; the difference between PU and ENJ is small between the four groups (about 3.30–3.54 and 3.31–3.42), the prompt "whether to give an explanation" has not significantly changed the baseline level of subjective experience; the overall trust is low (about 2.70–2.83), while the overall privacy concern is high (about 3.70–4.04), which is in line with the characteristics of "cautious and cautious" of college students towards small platforms. The selection overload mean is similar (about 3.43–3.60), which echo the subsequent "effect of list length is mainly reflected in the purchase intention rather than the obvious overload feeling".

The above descriptive results indicate that: on the one hand, the length of the list has a stabilising main effect on the purchase intention (the short list is better); on the other hand, the difference in the mean value of the interpretation on each indicator is limited, and it is difficult to change the intention or experience by relying on the general explanation text alone. Section 4.1 reports the t/F test and effect amount accordingly, verifies the main effect of "short > long" and explains that the main effect is not significant; Section 4.2 gives the regression mediation results of PU/ENJ (PU and ENJ significantly predict PI, but "explanation $\rightarrow$ PU/ENJ" is not significant); Section 4.3 shows the letter The interaction of any/privacy concerns is not significant, and the boundary of the conclusion is confirmed.

4.1. Main Effects (H1)

The explanatory reasons for providing personalized recommendations do not significantly improve subjects' subjective evaluations, which fails to support Hypothesis H1. In particular, the reasons for recommendations do not have a significant effect on purchase intention (with explanation $M = 3.40$, $SD = 1.03$; without explanation $M = 3.30$, $SD = 1.05$; independent samples $t(389) = 1.02$, $p = .312$). There were no significant differences between the two groups in perceived usefulness (with explanation $M = 3.50$, without explanation $M = 3.39$), pleasure ($M = 3.35$ vs 3.37), trust ($M = 2.75$ vs 2.78) and choice overload ($M = 3.57$ vs 3.51) ($p > 0.05$). This finding suggests that adding explanatory reasons to recommendations alone is not sufficient to significantly change consumer attitudes and experiences. In the context of this study, most subjects held a similar evaluation level of the recommendation even though they did not see the justification. This could be due to the fact that the information provided for the recommendation reasons is insufficient to persuade or influence the participants, with some even failing to notice the reasons altogether (the questionnaire results indicate that only around 70% of the participants accurately recognize the presentation of the recommendation reasons). As a result, the explanatory recommendation does not fulfill its intended purpose. In addition, subjects' overall trust in the platform is low (the overall mean value of trust is only about 2.76), which may limit the role of recommendation reasons in improving trust and purchase intention. In general, the effect of "explanatory recommendation is better than non-explanatory recommendation" as expected by H1 is not reflected in the data.

The length of the list has a primary effect as well as an overload effect. List length can have some effect on how subjects feel about making decisions. The two-factor variance analysis reveals that the long list significantly influences purchase intention more than the short list, indicating a notable main effect of list length on purchase intention ($F(1, 387) = 4.00$, $p < 0.05$). Specifically, in the case of long lists, $M = 3.30$, $SD = 1.04$; For the short list case, $M = 3.54$ and $SD = 0.99$, it feels better to buy some than the former. Therefore, it also proves that "too many choices will lead to a low willingness to make decisions. "In addition, although length does not reach a significant level for choice overload ($M(\text{short list}) = 3.50$, $M(\text{long list}) = 3.58$, $p = 0.462$), the average score of overload perception in the long list condition is higher than that in the short

list condition. In addition, under the condition of short list, the average score of experiencers 'pleasure evaluation is higher($M(\text{short list}) = 3.39$, $M(\text{long list}) = 3.32$). It is interesting that the main effect of list length on privacy concerns is not significant($p = 0.059$) within shortlist situation, subjects' privacy anxiety is somewhat stronger than that in the long list situation(shortlist $M 3.91$, longlist $M 3.74$). The participants' misreading of the short list indicated more precise suggestions with less content and realized their own products, which might be the cause of this. Therefore, it is likely that the participants are more aware of their privacy exposure and more concerned about privacy protection, which leads to the reverse of the result. But this is also a tipping point, and there may also be large differences across study groups. In addition to having no significant impact on purchase intention, the number of recommendations did not have a significant impact on subjects' subjective feeling other aspects(including but not limited to the effectiveness and pleasure of recommendations)($P > 0.05$). Moreover, there is no interactive effect between the amount of recommendation reasons provided and the length of the list within this range, which means that the two have independent effects on the outcome variables(effectiveness and pleasure).

Table 3. Main effects on purchase intention

Effect	DV	Test	p-value	Sig.
Explanation (Yes vs No)	Purchase intention (PI)	$t(389) = 1.02$	0.312	ns
List length (short vs long)	Purchase intention (PI)	$F(1,387) = 4.00$	<0.05	*

Note. This table reports the test results of the main effect of "whether to provide explanation of recommendation" and "length of recommendation list" on purchase intention. The results show that the main effect of explaining yes/no is not significant; Short lists (3-4) are significantly higher than long lists (10-12).

4.2. Mediation Tests (H2)

By increasing participants' perceived utility and pleasure, we think that personalized recommendation might have an indirect effect on purchase intention. Regression methods were used to investigate if perceived usefulness and pleasure were a mediating factor, which was done to test the H2 hypothesis. According to the results, the explanatory suggestion did not increase the perceived usefulness(M with explanation = 3.50 vs M without explanation = 3.39, $p = 0.236$) and pleasure(M with explanation = 3.35 vs M without explanation = 3.37, $p = 0.925$) of the subjects was not as effective as it was in terms of their perceived usefulness. However, at this point the scores of the two were lower. It doesn't match our presupposition. However, we also notice that the two have a considerably favorable effect on purchase intention at the same time; the two are significantly positive predictors of the purchase intention except for the difference of the experimental group at the total sample level; the multiple regression also found that, on average, each unit increase in perceived usefulness would result in an average increase in the corresponding purchase intention score of about 0.74 units($\beta = 0.74$, $p < 0.001$). In contrast, the impact of pleasure on purchase intention is weaker but there is still a significant difference($\beta = 0.14$, $p < 0.01$). When the above mediating variables are added to the regression model, it is found that the recommendation explanation still has a direct effect on the purchase intention, but this value is close to 0 and not statistically significant($\beta = 0.11$, $p = 0.312$ to $\beta = 0.03$, $p = 0.62$). Therefore, according to the data used in this study, there is no case that explanatory recommendation can make users' purchase intention stronger by using useful and pleasant. In summary, if the mediating effect of H2 is absent, the theory can only be considered partially validated. This means that even though the overall mediating effect may not be significant, some findings indicate certain alignments at the macro level. Specifically, presenting recommendations in a reasonable and engaging manner can enhance users

'perception of the recommendations and boost their intention to purchase. The reason for this may be that the information quality and presentation of the recommendation reasons are not enough to generate the corresponding purchase intention. In short, to get a positive response from users, improve the reasons for the recommendation.

Table 4. Summary of mediating effects (usefulness/pleasure → purchase intention)

Path/Effect	Estimate	p-value	Sig.
PU → PI	$\beta = 0.74$	<0.001	***
ENJ → PI	$\beta = 0.14$	0.010	**
Explain → PU ($\Delta M = 3.50 - 3.39$)	—	0.236	ns
Explain → ENJ ($\Delta M = 3.35 - 3.37$)	—	0.925	ns
Explain → PI (Before the mediation)	$\beta = 0.11$	0.312	ns
Explain → PI (After the mediation)	$\beta = 0.03$	0.620	ns

Note. Coefficients from multiple regression; ΔM denotes group mean differences. PU/ENJ are robust predictors, but explanation does not lift PU/ENJ, hence no overall mediation.

4.3. Moderation Tests (H3)

This study measures these two mediating factors by asking subjects about their trust in the reliability of personalized recommendations and their risk perception on privacy security and explores whether they will affect the effect of personalized recommendations on purchase intention through user trust or risk perception. The statistical findings indicate that there is no moderating effect between the two factors the interaction between participants 'trust and explanation does not significantly correlate with purchase intention ($p = .682$); likewise, the interaction effect of privacy concerns is also not significant ($p = .744$). The re-test results based on trust/privacy score showed that no significant difference was found in the mean difference of explained purchase intention between the two groups of participants with high and low trust scores ($p > .15$), and the mean difference of the samples within the corresponding groups of the two groups was only about 0.08(no explanation)/0.20(explanation). In summary, it can be concluded that when the trust/privacy of subjects is different, there is no difference in the interpretation degree of Hive mode. Thus, subjects who perceived high privacy concerns had the same attitude recommended in this study as subjects with low privacy concerns. H3 is not valid, indicating that user trust and user risk perception have no moderating effect on the path of H->P->B in this experiment. Perhaps because college students generally do not trust small e-commerce, there is no difference in trust, or because privacy is an extremely important and common issue in all samples (even though the average value of this indicator is only 3.8/5), which does not have so much impact compared with the change of high and low. Of course, it is also possible that some items of the scales such as trust, and privacy reflect their thoughts after seeing the recommendation information. The effect of the experiment has affected the original trust or privacy attitude of the subjects, so these variables cannot become independent moderating factors. In this case, it is necessary to measure the users 'trust or privacy preference before the experiment. This moderating effect can be tested more accurately.

In summary, the hypothesis testing of real data shows that straightforward recommendations do not significantly improve purchase intention or enhance college students 'trust in e-consumption. On the contrary, the longer the recommendation list is, the more burden of choice will be placed on consumers, which will slightly reduce their purchase intention. The mediation analysis reveals that enhancing consumers 'perceived usefulness and perceived pleasure is crucial; therefore, the recommendations from the current experiment do not address improvements in these two variables. Moreover, except for the few variables mentioned that differ in the degree of privacy or trust, other sorts of individual differences do not have any effect on the usefulness of recommendations. Therefore, based on this study, we can know that

in small and micro e-commerce platforms, only improving consumer experience can bring good consumer response, rather than shoving something into them.(That is, try not to simply increase the amount of recommendation or directly add reasons), pay more attention to the actual usefulness of the recommendation, and focus on highlighting its explanatory role, that is, not to explain for the sake of explanation, and do not completely lose its due role.

Table 5. Moderation analysis summary (Trust/privacy concerns × Explanation → Purchase intention)

Interaction	Effect size	p-value	Sig.
Explanation × Trust → PI	—	0.682	ns
Explanation × Privacy → PI	—	0.744	ns
Subsample mean difference (high trust vs low trust)	0.08 / 0.20; p>0.15	—	ns

Note. Interactions from models including main effects and cross-terms; subgroup checks corroborate the null moderation.

5. Conclusion

Based on "the influence of AI personalized recommendation on college students' consumption decisions on small e-commerce platforms", this study explores the effect and mechanism of AI personalized recommendation on consumption decisions to a certain extent through the combination of simulation experiment and questionnaire. The main conclusions include: First, AI personalized recommendation can effectively improve the purchase intention and purchase rate of student users, and AI personalized recommendation can increase user engagement and improve sales conversion; Second, the effective reason of AI personalized recommendation is not exactly to accurately match the needs of users, because it is also novel, interesting and worry free for users, so it will have a great impact on users' purchase behavior; Thirdly, there is also a problem that personalized recommendation may lead to impulsive consumption and trust dilemma, that is, recommendation may lead to irrational consumption impulse for students. Therefore, in view of this trust dilemma, it is necessary for the platform to integrate the degree of personalized recommendation with the user's own comfort. To sum up, this paper provides new empirical evidence and management implications on small e-commerce platforms and college students based on the verification of existing theories.

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