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E-commerce cart recommendation effects: A field experiment on entertainment products

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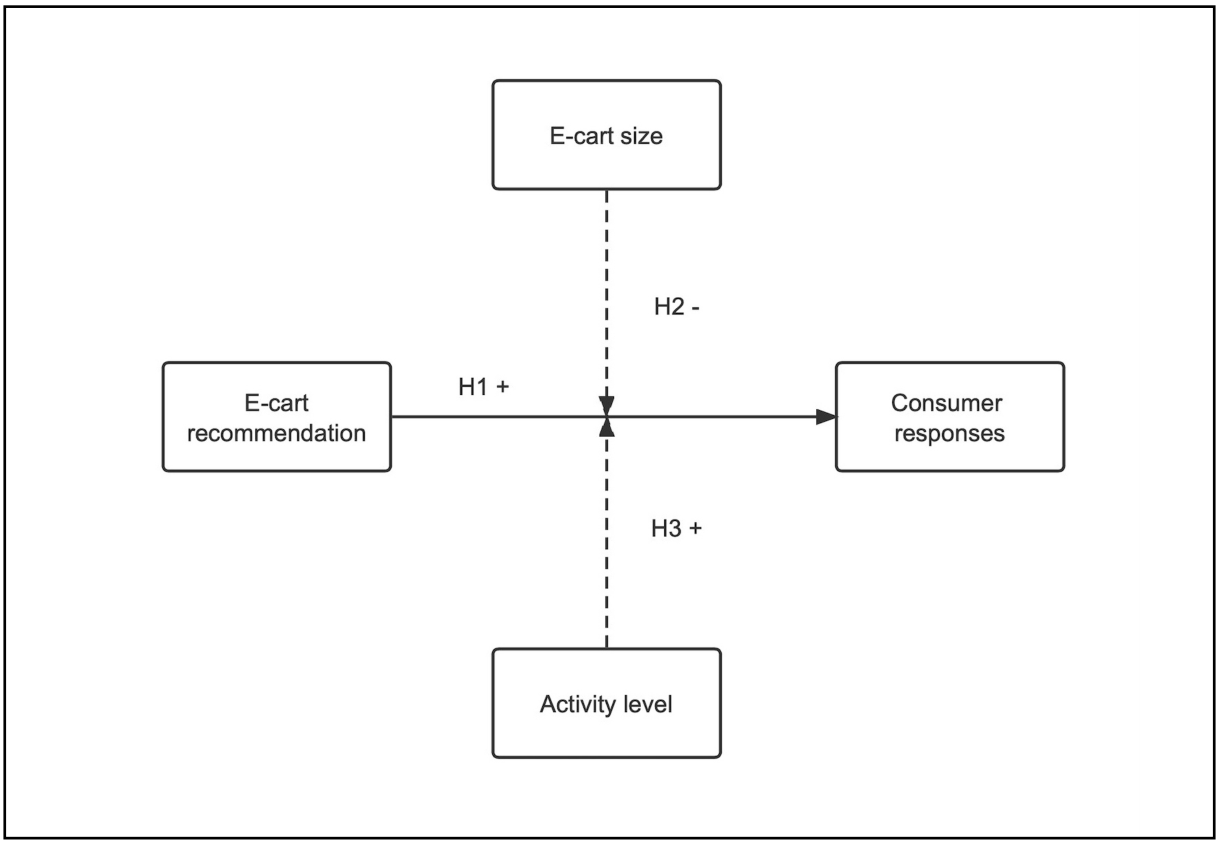
Graphical abstract



The effects of e-cart recommendation of entertainment products on consumer responses. All hypotheses are supported.

Public summary

■ This study explores the effects of e-cart recommendation on consumer responses in the field of entertainment products.

■ For entertainment products, e-cart recommendation has a positive impact on consumer responses relative to homepage recommendation.

■ The positive effect of e-cart recommendation declines when the cart is of more products.

■ The positive effect of e-cart recommendation increases when the recommended products are offered to more active consumers.

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Abstract: This study aims to compare the effects of e-cart recommendation and homepage recommendation in the field of entertainment products on the basis of a field experiment involving almost 13000 consumers supported by one of the leading digital reading platforms in China. The results indicate that e-cart recommendations have a significant positive impact on consumer downloads in comparison with homepage recommendations. Moreover, this positive effect decreases when the alternatives in the e-cart are of a larger quantity but increases when consumers are more active. Interestingly, this study also finds that e-cart recommendations can spill over to other products, leading to more downloads of non-recommended items. Our findings provide novel insights into consumer responses to e-cart recommendations of entertainment products for researchers and managers alike.

Keywords: e-cart recommendation; entertainment products; decision-making stage; field experiment

CLC number: F724.6; F713.36 **Document code:** A

1 Introduction

Advances in digital information technology and network carriers have recently promoted the explosive growth of entertainment products. For example, millions of novels are displayed on Wattpad, and hundreds of hours of videos are uploaded to YouTube every minute. Tens of millions of songs and more than 30 thousand brilliant playlists are offered to subscribers by Apple music. Although the endless stream of entertainment products enriches daily lives and expands the range of options, it also triggers the dilemma of information overload, which not only makes it more difficult for consumers to make choices but also leads to a low recommendation acceptance rate of companies.

To simplify complicated decision tasks, consumers tend to rely on a two-stage process in which they initially form a consideration set and then evaluate it in depth to reach final decisions[1–3]. For the sake of catering to the characteristics of the two-stage decision-making process and assisting consumers' selection of personal-like products, online platforms have long offered electronic carts (which we refer to hereafter as e-carts), which are available for consumers to aggregate information[4] and store products of interest[5, 6]. The virtual carts come in many forms, such as "cart" on Amazon and "Library" on Wattpad.

Aside from supporting consumer decision-making with homepage recommendations[7–11], considerable platforms, especially online shopping platforms, currently utilize e-cart recommendations for practical and search products. For instance, major e-commerce businesses such as Taobao, JD.com, Suning, Tesco, and Lifease directly suggest products that consumers may be interested in the e-cart. Although some entertainment platforms, such as iReader and QQ Reader, have adopted the e-cart recommendation strategy to achieve better recommendation performance, some entertainment platforms, covering the field of online novels and videos, have not yet taken this strategy into account. It is reported that the scale of China's entertainment market reached ¥ 224.35 billion in the first two quarters of 2020[12]. In 2020 alone, the number of products in one of the subdivided fields, online novels, reached 27.94 million in China[13]. In view of the lack of practice of e-cart recommendation in the field of entertainment products and the rapid development of the entertainment market, it is necessary to determine whether and how e-cart recommendation affects consumers' responses to entertainment products. Academically, extant research concerning the effects of e-cart recommendation mainly focuses on nonentertainment products, such as digital cameras and shampoos[14, 15]. In our context, we focus on entertainment products that are preproduced and delivered via media[16]. They are hedonic and experiential and are all about directly providing consumers with multisensory experiences[16–18]. Their characteristics differ essentially from those of practical and search items in that they are more subjective, intangible, and symbolic[19]. Additionally, the benefits and quality provided by entertainment products are more difficult to assess and quantify[20, 21]. Given that product attributes are able to influence the effectiveness of recommendations[7, 19, 22], previous findings may not be applicable to entertainment products, which makes the use of this strategy by entertainment platforms lack a theoretical basis. Therefore, we attempt to deeply explore the effects of e-cart recommendation of entertainment products to extend the study of recommendation and entertainment consumption. Taken together, investigating the recommendation effects of entertainment products is of practical and academic significance. In this study, we attempt to answer the following questions:

(Ⅰ) How does the effect of e-cart recommendation compare with that of homepage recommendation in the field of entertainment products?

(Ⅱ) What factors have impacted on e-cart recommendation effects?

Inappropriate recommendations cannot achieve the expected effects[23, 24], nor can they promote the benign development of the market. Owing to the wearout and annoyance of consumers caused by repeated and frequent product exposures[25, 26], repeated recommendations of the same products, such as the simultaneous use of homepage recommendation and e-cart recommendation, may not be an effective method. Thus, we make a comparison between the effects of two forms of recommendation, aiming to provide more recommendation scenarios and value verification of e-cart recommendation for managers of entertainment products. Using a detailed data set from a leading Chinese reading platform, we attempt to explore the effects of e-cart recommendations on consumers' responses. Specifically, we conduct a field experiment to compare the differences in downloading behavior on the recommended novel across two groups. Consumers in the treatment group are those who receive the recommended novel in their e-carts. The control group's consumers received the recommendation on the homepage. In addition, we examine whether the effect of e-cart recommendation is moderated by two factors, namely, e-cart size and consumer activity level.

Our research contributes to the literature and marketing practices in three key ways. First, our study provides empirical support in the field of entertainment products for how e-cart recommendations impact consumers' responses. As the research and practice of e-cart recommendation for entertainment products are insufficient, entertainment platforms that attempt to use this strategy lack a theoretical basis and reference examples. Our research not only enriches the literature on recommendation as well as entertainment consumption but also confirms the value of e-cart recommendation and provides more recommendation scenarios for managers of entertainment products. Second, our work empirically examines the moderating effects of the impact of e-cart recommendation and thus generates useful insights for online businesses interested in deploying this marketing strategy. Third, our study explores the spillover effect of e-cart recommendations on other non-recommended products. Therefore, managers should consider multifaceted effectiveness when selecting an appropriate recommendation strategy.

The rest of this paper is organized as follows. Section 2 provides an overview of the relevant literature. Section 3 develops three hypotheses, followed by the experiment and data description in Section 4. The hypothesis test results and robustness check results are discussed in Section 5. Section 6 concludes with a discussion of the findings and contributions as well as limitations and suggestions for future work.

2 Literature review

2.1 Entertainment products

Driven by technological progress and growing consumer demand, entertainment is rapidly burgeoning and has substantial impacts on the economy and consumer well-being. Examples include novels, movies, music, and TV series. Entertainment products, hedonic and experiential in nature, can directly give people emotional pleasure[16–18]. Their characteristics are intangible and symbolic[19]. In reality, most entertainment products, such as online novels and movies, are usually described by genre, a commercially defined attribute that neither reflects consumer perceptions[17] nor offers adequate granularity and richness[27]. Indeed, it can only be used to describe a type of product rather than a single, specific product[16]. Hennig-Thurau and Houston[16] and Foutz[17] argue that measuring the quality and experience of entertainment products that are experiential and informational is challenging. Entertainment consumption is usually associated with hedonic and affective motivation[28–31]. When facing products in the entertainment category, consumers want to seek pleasure and enjoyment[16, 28, 32] and prefer items that satisfy their psychological needs[27]. In this sense, the choices of entertainment products rely heavily on individual preference. However, coarse-grained description, such as genre, is incapable of conveying entertainment products' detail, making it difficult for consumers to determine whether the products satisfy their expectations.

2.2 Two-stage decision-making theory

Consumers find it easier to approach a vast number of products, particularly online. However, they are often incapable of evaluating all available alternatives in depth prior to making a choice[1, 33] since considerable cognitive effort is required to compare and evaluate a large set of alternatives[8, 34]. To simplify complicated decision tasks, consumers tend to rely on a two-stage process. At the initial stage, consumers typically screen plenty of available products and identify a subset of the most promising ones; at the later stage, consumers compare and evaluate products added in the subset to make final choices[1–3, 33]. To cater to consumers' two-stage decision-making tendency, online platforms provide consumers with e-carts that can be used to aggregate information[4] and place products of interest for further evaluation and potential subsequent purchase[5, 6].

2.3 Homepage recommendation and e-cart recommendation

Homepage recommendation is one of the earliest forms of recommendation used in practice. Research concerning this topic has featured prominently in the field of consumer behavior in recent years. Evidence from a series of choice experiments conducted by Senecal and Nantel[7] showed that online product choices of consumers as well as satisfaction and loyalty are significantly influenced by recommendations. Consumers who consult product recommendations have a much greater possibility of choosing the recommended item than those who do not. Xiao and Benbasat[8] pointed out that recommendation can improve consumers' confidence in choice

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and reduce decision-making efforts. Through a randomized field experiment, Lee and Hosanagar[9] found that recommendations generated by collaborative filtering recommenders are associated with an increase in individual consumption diversity. Lee et al.[10] noted that consumers respond more positively to recommended products, which is reflected in more product purchases and views and higher rates of click-through and conversion. Moreover, Chinchanachokchai et al.[11] proved that recommendation plays an important role in consumers' choice satisfaction.

The decision-making process is typically characterized by two stages[1–3]. In different phases, consumers' responses to product recommendations vary obviously[35]. Although research focusing solely on e-cart recommendation is sparse, a narrow stream of research regards homepage and e-cart recommendation as the first- and second-stage recommendations, according to the two-stage decision-making process and compares their effects. Shi et al.[14] revealed the differences in decision difficulty of electronic product recommendations of consumers at different stages. The results showed that electronics that belong to utilitarian and search products are less likely to be considered when they are recommended in the e-cart. Simulating an online shopping site in the laboratory, Yan et al.[15] demonstrated that consumer acceptance of product recommendations alters according to decision-making stages. Consumers tend to accept the recommendation of similar products on the homepage. However, they prefer the recommendation of related products on the e-cart page.

Although extant research has begun to study these two ecommendation forms together, it has yet to reveal the differences in consumer responses in the real context of entertainment products. It is crucial because product attributes can influence recommendation effects[7, 19, 22] and the entertainment industry is continuously expanding[12, 13]. We advance the previous literature by leveraging a field experiment on a reading platform to compare the effects of homepage recommendation and e-cart recommendation.

3 Hypothesis development

Goals and preferences of consumers usually change from being abstract to more precise in the progress of decision-making[3, 36–38]. To better serve consumers and help them find their favorite products more efficiently, platforms provide not only e-carts for storage[4–6] but also recommendation services[1, 10, 14, 39], including homepage recommendations and e-cart recommendations. At the first decision-making stage, consumers are mainly active on the homepage and are relatively directionless[36] with preference uncertainty[14]. They browse widely on the homepage and conduct searches, trying to narrow the target scope[38]. In addition, they add products of interest to their e-carts and receive homepage recommendations[15]. At the second stage, consumers mostly remain active in e-carts and possess clearer goals and preferences[15, 40]. They make evaluations and comparisons among items to reach decisions and obtain e-cart recommendations.

Entertainment products, hedonic and experiential, cannot be readily broken down into a set of specific properties. The majority of them, such as online novels, are usually described by symbolic and category-level attributes such as genre. Consumers often tend to assess products by matching their needs with product information[41]. However, in regard to entertainment products with abstract attributes on the homepage at the first decision-making stage, the recommended items are not easily acceptable to consumers. Because consumers possess only relatively ambiguous objectives and preferences, they are uncertain about whether the homepage recommendations actually match their targets. In the e-cart, consumers have cleared their goals and formed individual tastes through experience. They can quickly filter useful information to adapt to platform activities and are more willing to make positive responses correspondingly[42]. Therefore, they are more susceptible to recommendations[15]. Taken together, compared with being recommended on the homepage, an entertainment product is more likely to be selected when it is recommended in the e-cart. Therefore, we hypothesize the following:

H1. For entertainment products, e-cart recommendations have a positive impact on consumers' responses relative to homepage recommendations.

We define e-cart size as a descriptive characteristic that provides information about how many products are included in the cart. Understanding how the same recommendation may exert different persuasive effects depending on the number of items in the e-cart is critical since consumers are cognitive misers who are usually averse to considering many options[43]. Contrary to the intuition that more choice is always better, there exist two major negative consequences associated with choosing from a large set, less choice[44–46] and the other is purchase probability reduction[25, 47]. Iyengar and Lepper[44] demonstrated that increasing the number of options hampers consumers' later motivation to select and purchase when compared with contexts that offer a limited array of choices. Reasons behind these counterintuitive results can be drawn from prior studies. First, saliency to a large degree determines the ability of visual objects to attract attention[48, 49] and can influence the recommendation effect[50]. When the e-cart is large in size, it is difficult for the recommended product to stand out and stimulate consumers to behave in the desired ways. Second, as the quantity of choices increases, the complexity and difficulty of the decision also amplify, leading to more trade-offs consumers need to consider[34, 47] and more cognitive effort consumers need to exert[10, 34, 43, 45]. In this case, consumers retain hardly any cognitive resources for processing other information (e.g., recommended products)[51]. Conversely, a limited-choice condition facilitates the effective exposure of the recommended product, as a small set is able to restrict consumers' concentration to items within the set[52]. Additionally, the smaller the choice set size is, the easier the decision[33]. Consumers who are involved in relatively simple tasks that do not exert high demand on processing capacity will pay more attention to other stimuli[53, 54] and have a higher tendency to choose[44]. Taken together, we hypothesize the following:

H2. The positive effect of e-cart recommendation declines when the cart is of more products.

In addition to cart characteristics, individual factors are of equal importance in affecting consumers' decision-making[3, 55–58]. Previous studies center on the importance of activity level in explaining consumers' interests as well as purchases and demonstrate that active consumers purchase more[10, 59]. A more recent study distinguishes low active consumers from high active consumers and finds that more active consumers are more attracted to e-retailers as they use e-coupons more often[60]. This line of research suggests that more active consumers can be considered those who interact more with products, and consumers with high activity levels more easily generate interest in and positively become involved in launched campaigns. Thus, we expect that consumer activity level could amplify the positive effect of e-cart recommendation and hypothesize the following:

H3. The positive effect of e-cart recommendation increases when the recommended product is offered to more active consumers.

Fig. 1 illustrates our proposed research model.

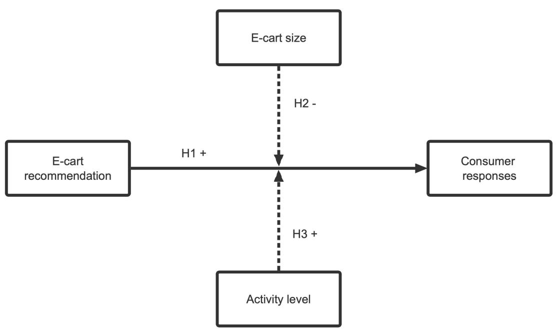

Fig. 1. Proposed research model.

4 Background and research design

To test the hypotheses, we chose online novels to represent entertainment products and conducted a field experiment in collaboration with a leading Chinese digital reading platform (hereinafter referred to as the platform) in July 2019. The platform provides more than 500000 reading content across diverse genres, such as romance, fantasy, mystery, and horror. It targets a wide variety of consumers and currently has approximately 160 million active monthly consumers. Most novels on the platform, containing thousands of chapters, are published in a serialized format and charged by chapter. Generally, the average price per chapter is ¥ 0.1–¥ 0.2①. In addition, the platform provides packaged purchase services that allow consumers to purchase dozens of chapters at a time. However, because there are too many chapters in a single novel and consumers are uncertain about the reading content, most consumers prefer to buy by chapter. Similar to other reading platforms, the platform supplies both homepage and e-cart interfaces. On the homepage, consumers can widely browse and search as well as download and preview novel content. Whenever they encounter novels of interest, consumers can add them to their e-carts. The platform can recommend novels on these two pages.

In the previous literature, when comparing the effects of e-cart recommendation with homepage recommendation, the traditional experimental design is to make product recommendations to the same consumer twice in a shopping session according to the two-stage decision-making process[14, 15]. However, consecutive recommendations can produce duplicate effects, which will influence the accuracy of the results. This paper optimizes the experimental design to avoid this problem. After an observation of the platform, we find that consumers at the first stage mainly stay on the homepage for extensive browsing and tend to download a small number of chapters per novel; consumers at the second stage are primarily active in the e-cart and inclined to download more chapters per novel. Moreover, the platform stipulates that consumers will enter the page they left before by default when they enter the platform. Based on the above, we randomly select tens of thousands of individuals from the consumer database and divide them into two groups according to the interface where consumers last close the application. The treatment group includes consumers who close the application on the e-cart page. The next time they open the application, they will receive a recommended novel that is presented on a card② at the top of the e-cart interface. The control group is consumers who close the application on the homepage. Thus, they will receive a personalized recommended novel in a top card of the homepage. Fig. 2 illustrates the different formats. We also analyze the average downloads per novel of the two groups. The results show that the average number of downloaded chapters per novel of the treatment group is significantly higher than that of the control group. However, comparison between these two groups of consumers may be invalid because consumers can self-select the interface where they last close the application. To verify the correctness of our findings, we conduct further tests in Section 5.2, and the results remain consistent.

The platform uses the same recommendation algorithm and recommendation pool to make recommendations to the two groups. Specifically, the algorithm calculates consumer preference propensity for the novels in the recommendation pool according to consumer behavior records and recommends the novel with the highest preference propensity to consumers. We check whether the two groups differ in any important metrics involved in the algorithm in the following part. The test results in randomization check indicate that there is no significant difference. Additionally, we find no difference in the distribution of recommended novels between the two groups. All these results verify the randomness and rationality of the experiment. The main purpose of this experiment is to explore the role of e-cart recommendation in entertainment products through a comparison between the effects of homepage and e-cart recommendations. A stream of literature has noted that price can significantly influence consumer decision-making[61–63] and the effects of recommendation[10, 64]. Therefore, to control the confounding influences caused by price, all novels involved in the experiment are free. Taken together, through this experiment, we are able to gauge how much and in what direction e-cart recommendation, compared to homepage recommendation, affects consumer download

① According to the billing mode of the platform, each chapter of a novel is billed in words, usually ¥ 0.03–¥ 0.05 per 1000 words.

② Card is a kind of UI component which can contain related pieces of information. It is widely used in the software-design world.

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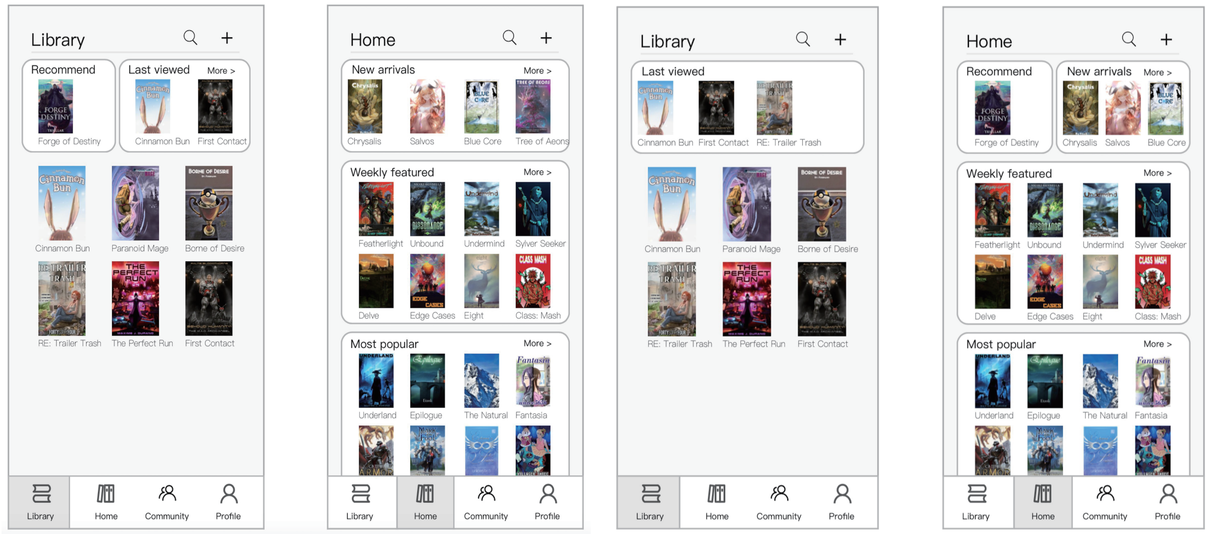

(a) E-cart recommendation

(b) Homepage recommendation

Fig. 2. Example of recommendation in different groups.

behavior.

For the empirical investigation, the platform offered consumer past behavioral records and data on demographics①. The time window of the data collected covers two periods: one month before and after the experiment. Online novel reading is one of the methods of entertainment that may not always be included in one's daily routine. This means that consumers of the platform may not log in frequently. Thus, consumers' responses toward platform activities may require some time to materialize. Moreover, novels participating in the experiment have an average of 2403 chapters, which require a commitment of time for reading. Indeed, we find that some consumers read the recommended novel for nearly 30 days. Therefore, to capture consumer behavior as much as possible, ensure the integrity of their behavior and make the data before and after the experiment corresponding and comparable, we set the time window to 1 month. Our final sample consists of 12872 consumers, of which 6377 are in the treatment group and 6495 are assigned to a control group.

In Table 1, we report variable definitions as well as descriptive statistics. Since the recommended novels in the experiment are free, we use downloads to measure consumer acceptance. In addition, to construct the individual moderator, we follow Knuth et al.[59] who proposed that activity level was the amount of interaction between consumers and products. On the reading platform, downloading is one of the main interactive behaviors between consumers and products. Thus, we utilize the number of novels consumers have downloaded within one month before the campaign as a measurement of activity level. In Table 2, we present the randomization check results comparing the pretreatment activity for each group. Table 2 indicates that our treatment and control groups do not statistically differ in any important metrics before the experiment. Therefore, the data passed the randomization check.

We next present model-free evidence that e-cart recommendation leads to a change in consumer downloading responses in contrast to homepage recommendation, as shown by whether consumers downloaded the recommended novel. Fig. 3 illustrates how downloading responses alter across two groups of consumers. As shown, there is an obvious increase in the average downloads of treated consumers on the recommended novel compared to those of controlled consumers. This pattern is consistent with our expectation that e-cart recommendation is more effective in engendering consumer responses.

5 Analyses and hypothesis test results

We then describe how we model and estimate the effects of e-cart recommendation on consumer downloading responses using field experiment data.

5.1 Main results

Given that the outcome variable is a binary variable, we apply the Logit model to estimate how recommending a personal-like novel j in the e-cart or on the homepage impacts consumer i's downloads of this novel. The model specification is as follows:

$$\mathrm{Downloadprobability}_{ij} = \frac{\exp(Y_{ij})}{\exp(Y_{ij})+1},$$

$$Y_{ij} = \beta_0 + \beta_1 \mathrm{Treat}_i + \beta_2 \mathrm{Consumer}_i + \beta_3 \mathrm{Novel}_j + \varepsilon_{ij},$$

where Y_{ij} is the dependent variable that indicates download decision, namely, $\mathrm{Download}_{ij}$. Treat_i is the independent variable. We also control for consumer as well as novel related factors ($\mathrm{Consumer}_i$, Novel_j). Consumer-related variables, including Gender, Nickname, (Phone type), and (Registration duration), are used to control the potential impacts of individual-level factors on consumer download responses. In terms of novel related variables, we include Category, Update, and Heat to control the potential impacts of novel classification, degree of completion and popularity. In addition, we

① The research data used in this study is confidential and unsuitable to post due to its sensitive nature.

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Table 1. Main variables summary.

Variable name	Variable description	Mean	SD	Min	Max
Download	Dummy to indicate whether a consumer downloaded the recommended novel within one month after the recommendation campaign; Download = 1 for downloaded, and 0 otherwise.	0.60	0.49	0	1
Treat	Dummy to indicate whether a consumer is in treatment group or control group; Treat = 1 for treatment group, and 0 otherwise.	0.50	0.50	0	1
E-cart size	Number of novels in consumer's e-cart.	3	5.40	0	140
Activity level	Individual activity level of a consumer.	5.47	10.82	0	279
Pre_download chapters	Number of chapters a consumer downloaded within one month before the activity.	231.10	952.26	0	26724
Pre_download days	Number of days a consumer downloaded within one month before the activity.	3.49	5.33	0	31
Pre_pay novels	Number of novels a consumer paid for within one month before the activity.	0.48	1.20	0	18
Pre_all pay	Total amount paid by a consumer within one month before the activity.	2.36	10.06	0	268.51
Pre_pay days	Number of days a consumer paid within one month before the activity.	1.42	4.22	0	31
Gender	Dummy to indicate gender; Gender = 1 for female, and 0 otherwise.	0.40	0.49	0	1
Nickname	Dummy to indicate whether an account has a nickname; Nickname = 1 for having a nickname, and 0 otherwise.	0.30	0.46	0	1
Phone type	Dummy to indicate mobile phone type; Phone type = 1 for iPhone, and 0 otherwise.	0.25	0.43	0	1
Registration duration	Length of consumer registration (unit: day).	442.40	361.43	1	2449
Category	Dummy to indicate novel category; Category =1 for female channel, and 0 for male channel.	0.52	0.50	0	1
Update	Dummy to indicate novel update status; Update = 1 for being updated, and 0 otherwise.	0.93	0.25	0	1
Novel chapters	Total number of chapters of a novel.	2403	1341.91	604	4805
Novel words	Total number of words of a novel.	5356973	3005694	1458526	12047318
Heat	Number of consumers recommending a novel.	229.50	316.46	0	1509

Table 2. Randomization check.

	Observations	Pre_download chapters	Pre_download days	Activity level	Pre_pay novels	Pre_all pay	Pre_pay days
Treatment group	6377	233.08	3.45	5.45	0.48	2.27	1.40
Control group	6495	229.12	3.53	5.49	0.47	2.45	1.43
p value	N/A	0.81	0.37	0.85	0.49	0.31	0.71

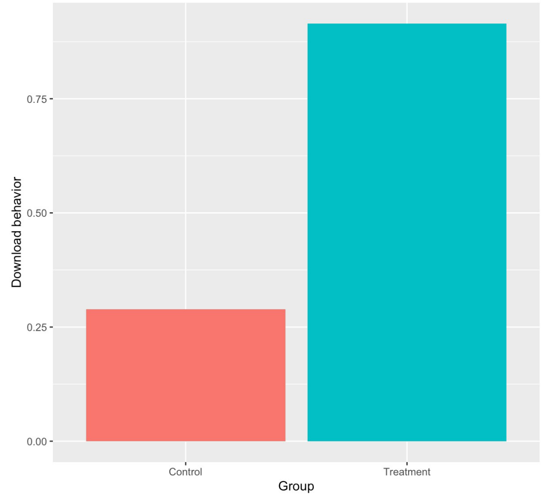

Fig. 3. Model-free evidence for the download behavior of treatment and control.

include (Novel chapters) and (Novel words) to control the impacts of novel length from two dimensions. ε_{ij} is the error term.

Table 3 displays the estimation results of various model specifications: we only consider the treat effect on downloads in column (1) and further control the consumer effects and novel effects in column (2). The results suggest that the coefficient of Treat is positive and statistically significant (3.27, $p < 0.001$; 3.29, $p < 0.001$). Thus, compared with recommending a personal-like novel on the homepage, consumer downloads increase significantly when the novel is recommended in the e-cart. Hypothesis 1 is supported. We also find that female consumers have a higher download intention for e-cart recommendations than males, and novel recommendations in the female channel are more likely to be downloaded. R^2 is relatively stable before and after the control variables are included, providing further support for the role of Treat in capturing consumer downloads of e-cart recommendations.

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Table 3. Main results.

Dependent variable	Download Logit (1)	Download Logit (2)
Treat	3.27 ***	3.29 ***
	(0.05)	(0.05)
Constant	−0.90 ***	−1.04 ***
	(0.03)	(0.10)
Consumer		
Gender		0.23 ***
		(0.06)
Nickname		0.10
		(0.06)
Phone type		−0.06
		(0.07)
Registration duration		−0.02
		(0.03)
Novel		
Category		0.17 *
		(0.08)
Update		−0.06
		(0.09)
Novel chapters		−0.18
		(0.16)
Novel words		0.22
		(0.15)
Heat		−0.05
		(0.04)
R^2	0.41	0.42
Observations	12872	12872

$p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

5.2 Robustness check

To prove that our main results are not affected by consumer self-selection, we reestimate column (2) in Table 3 using a redefined independent variable that is constructed according to consumer downloading characteristics. Specifically, based on the fact that consumers download more chapters per novel when they are active in the e-cart compared with on the homepage, we utilize the average number of downloaded chapters per novel by consumers to predict their probability of accepting a recommended novel in the e-cart through the Logit model. Treat equals 1 when the predicted probability from the Logit regression is greater than the ratio of the selection to all choices; otherwise, it equals 0. The results presented in Table 4, column (1) are consistent with the main results.

In our main models, we use download decisions with a value of 1 or 0 as the dependent variable. However, aside from download decision, our data can also measure the effects with download amount (the number of downloaded chapters of the recommended novel). Thus, we run a Tobit model with (Download chapters) as the dependent variable. The results are listed in Table 4, column (2) and column (3).

Table 4. Robustness check for main results.

Dependent variable	Download logit (1)	Download chapters Tobit (2)	Download chapters Tobit (3)
Treat	0.22 *	187.30 ***	189.00 ***
	(0.09)	(4.77)	(4.81)
Constant	−0.05	−178.40 ***	−184.60 ***
	(0.08)	(3.90)	(10.07)
Consumer	Yes	No	Yes
Novel	Yes	No	Yes
R^2	0.02	0.02	0.02
Observations	12872	12872	12872

$p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Consistent with our main findings presented above, both the coefficients of Treat are positive and statistically significant (187.30, $p < 0.001$; 189.00, $p < 0.001$). Thus, these results provide additional empirical evidence in support of H1.

5.3 Moderating effects

To examine the moderating effects of e-cart size and individual activity level, we estimate a Logit model as follows:

$$\text{Downloadprobability}_{ij} = \frac{\exp(Y_{ij})}{\exp(Y_{ij})+1},$$

$$\begin{aligned} Y_{ij} = & \beta_0 + \beta_1 \text{Treat}_i \times (\text{E-cart size})_i + \beta_2 \text{Treat}_i \times \\ & (\text{Activity level})_i + \beta_3 \text{Treat}_i + \beta_4 (\text{E-cart size})_i + \\ & \beta_5 (\text{Activity level})_i + \beta_6 \text{Consumer}_i + \beta_7 \text{Novel}_j + \varepsilon_{ij}, \end{aligned}$$

where Y_{ij} is the dependent variable, Download_{ij}, $(\text{E-cart size})_i$ and $(\text{Activity level}_i)$ are the two moderating variables. The results in column (1) of Table 5 show that the coefficient of Treat×(E-cart size) is negative and significant (–0.48, $p < 0.001$) and that of Treat×(Activity level) is positive and significant (0.11, $p < 0.1$). Thus, as the quantity of options in the e-cart increases, consumers are less likely to select the item that is recommended in the cart. In contrast, the activity level of a consumer significantly improves the choice of this recommended product.

Furthermore, we use the number of chapters rather than novels consumers have downloaded within one month before the campaign to indicate activity level and run a Tobit model with download chapters as the outcome variable to assess the moderating effects. The results shown in Table 5, column (2) are consistent with previous findings, thus providing further evidence for H2 and H3.

5.4 Spillover effects

To demonstrate the important role of e-cart recommendation, we take a step forward to use two other dependent variables in model 2, (Other download) and (All download), and obtain spillover effects. These two dummy variables represent whether a consumer downloaded novels except or including the recommended one within a month after the activity, respectively. Column (1) and column (2) in Table 6 report the

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Table 5. Moderating effects.

Dependent variable	Download Logit (1)	Download chapters Tobit (2)
Treat×(E-cart size)	−0.48 ***	−30.16 ***
	(0.06)	(3.81)
Treat×(Activity level)	0.11	26.41 ***
	(0.07)	(3.22)
Treat	3.32 ***	189.20 ***
	(0.05)	(4.81)
E-cart size	0.31 ***	23.07 ***
	(0.06)	(5.34)
Activity level	−0.01	0.92
	(0.06)	(3.47)
Constant	−1.04 ***	−184.00 ***
	(0.10)	(10.04)
Consumer	Yes	Yes
Novel	Yes	Yes
R^2	0.42	0.02
Observations	12872	12872

$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

estimation results. Both the coefficients of Treat are positive and significant (1.51, $p < 0.001$; 2.96, $p < 0.001$). Thus, although not hypothesized, we find that e-cart recommendation also promotes consumer responses to other products. This finding supports prior research that product recommendations can spill over to other nonrecommended products[65].

We further run a Tobit model with (Other download chapters): monthly download chapters of novels other than the recommended one and (All download chapters): monthly download chapters of all novels as the outcome variables to check the spillover effects. The results shown in Table 6, column (3) and column (4) remain consistent.

Table 6. Spillover effects.

Dependent variable	Other download Logit (1)	All download Logit (2)	Other download chapters Tobit (3)	All download chapters Tobit (4)
Treat	1.51 ***	2.96 ***	54.49	102.20 ***
	(0.06)	(0.11)	(30.15)	(29.96)
Constant	2.48 ***	2.94 ***	278.20 ***	283.80 ***
	(0.16)	(0.19)	(64.77)	(64.60)
Consumer	Yes	Yes	Yes	Yes
Novel	Yes	Yes	Yes	Yes
R^2	0.18	0.26	0.02	0.02
Observations	12872	12872	12872	12872

$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

6 Conclusions

For the sake of better assisting consumers in making choices in the face of massive options, many e-commerce practitioners, involving entertainment product providers, recommend products of consumers' interest in the e-carts. Although this increasingly vibrant form of recommendation has become a trend, there is a lack of in-depth investigation on it, let alone the potential moderating effects. Using a detailed data set from a field experiment involving almost 13000 consumers, we compare the changes in downloading responses across two groups of consumers: consumers of the treatment group who receive the recommended novel in their e-carts and consumers of the control group who receive the recommendation on the homepage. Our empirical analysis shows that e-cart recommendation has a significant positive impact on consumer downloading responses. An obvious increase in downloads of the recommended novel is revealed. In addition, we find that this positive effect weakens when the e-cart is of a larger size but enhances when consumers are more active. Furthermore, our results demonstrate that e-cart recommendations can spill over to other non-recommended products.

6.1 Theoretical implications

Our findings offer several important theoretical implications. First, our research examines the effects of e-cart recommendations on consumer responses in the field of entertainment products. Although promising, extant research related to this topic pays more attention to nonentertainment products and concludes that products recommended on homepages are more accepted than those recommended in e-carts[14, 15]. However, different types of products vary in characteristics, provide diverse benefits and experiences to consumers[16–19], and trigger different recommendation effects[7, 19, 22]. Thus, it is necessary to extend the current studies by exploring the effects of e-cart recommendation of entertainment products. Utilizing a detailed experimental data set, we find increased consumer downloading responses in reaction to e-cart recommendations for entertainment products compared with homepage recommendations. Our findings on the effectiveness of e-cart recommendation on entertainment products offer evidence for an important subject of considerable practical purpose in e-commerce.

Second, we add to the extant literature regarding the impact of cart characteristics[66] and consumer activity level[10, 60] on consumer responses toward managerial actions. In contrast to previous studies centering on either element, our research examines both holistically. Our findings highlight the importance of considering contextual factors and individual factors in evaluating the comprehensive effect of e-cart recommendation.

Third, our research exploratively uncovers the spillover effect of e-cart recommendation. Consistent with previous findings that product recommendations can spill over to other nonrecommended products[65], we find that in the context of entertainment reading, e-cart recommendation is able to promote the downloads of not only the recommended novel but also other novels. This is critical because the effectiveness of

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a marketing strategy can be better evaluated through multiangle analysis.

6.2 Managerial implications

Our study also provides several important managerial implications. Due to the lack of practice and research on e-cart recommendation in the field of entertainment products, entertainment platforms' awareness of this strategy is relatively insufficient. Our findings provide managers of entertainment products with insights into their value and more recommendation scenarios. The successful application of e-cart recommendation in the field of entertainment products will help promote the healthy development of the entertainment market. Furthermore, our results also provide managers with concrete guidance on how to employ e-cart recommendations with greater effect. First, it is pivotal for online platforms to take consumer decision-making stages into account. Consumers at different stages vary in many aspects, such as goals[3, 36]. These divergences may contribute to the apparently different responses of consumers toward recommended items[37, 38]. Thus, e-commerce platforms should make an appropriate match between specific recommendation tactics and stages of consumer decision-making.

Additionally, inopportune or inappropriate recommendations can trigger failure to achieve the desired effects[15, 23, 24]. Without considering the moderating roles of cart and individual characteristics, platforms may miscalculate the potency of e-cart recommendation. Instead of aimlessly targeting consumers at large, managers should differentiate them according to the moderating factors discussed above before deploying e-cart recommendations. Our results show that for more active consumers with smaller e-carts, e-cart recommendation works better. Therefore, strategically, platforms can remind consumers to organize and clean their e-carts and increase consumer activity levels through interesting campaigns.

Finally, marketing actions call for a comprehensive assessment of their effects. While responses toward the recommended products are often a first-order concern for platforms trying to validate and optimize their marketing strategies, it is necessary to consider whether a tactic impacts other outcomes, such as choices of other products.

6.3 Limitations and future work

Our research has several limitations that indicate avenues for future research. First, our study is confined to the e-commerce environment of China. The findings reported here may not be generalizable to other countries due to cultural differences. Thus, we call for future research to further expand the scope of empirical analysis to other countries' e-commerce contexts. Second, although our research finds the causal effect of e-cart recommendations on consumer downloading responses through a field experiment, we fail to reveal the underlying mechanism. Additional research is needed to investigate the potential related psychological mechanism. Third, to study the effects of e-cart recommendation of entertainment products, we choose free online novels as research objects to control the possible confounding influences caused by price. There is a need for future research to focus on paid products. Finally, our research on e-cart recommendation is based on two-stage decision-making theory and thus follows the research methods in previous literature to treat homepage recommendation as the control group[14, 15]. Future research can regard consumers without any recommendations as the control group to further explore the effects of e-cart recommendations. To conclude, our research offers insight into the impact of e-cart recommendations on consumer responses. We hope that our study provides a foundation and encourages future research in this pivotal field of e-commerce.

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Conflict of interest

The authors declare that they have no conflict of interest.

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