The 3rd International Conference on Educational Innovation and Philosophical Inquiries (ICEIPI 2022)
DOI: 10.54254/2753-7048/3/2022523

The Impact of Personalized Recommendation on Digital Satisfaction of Users

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Abstract: Although personalized recommendation system is widely applied on various platforms and commercial websites, fewer studies have examined the impact of personalized recommendations on digital satisfaction and the experience of users from their perspective. Will the attitude toward personalized recommendations affect digital satisfaction? Why do some people hold a negative attitude towards personalized recommendations? This study uses the quantitative research methods of questionnaires to collect data with a sample size of 1002. The result shows that there is a positive correlation between the attitude toward personalized recommendations and digital satisfaction. Approximately 25.4% of participants reported that they do not prefer personalized recommendations who are senior people having a low sense of media literacy and online experience with lower information overload. This article adopts information overload theory and user involvement theory to explain the correlation between personalized recommendation and digital satisfaction involving the discussion of its advantages and disadvantages, attempting to call attention to the neglected Generation X.

Keywords: personalized recommendation, algorithm, digital satisfaction, privacy, information overload, generation x.

1. Introduction

In the era of social media, with the help of algorithm personalized recommendations are becoming prevalent. Personalization refers to providing customized and personalized services based on customer-provided user profiles during transactions with firms [1]; in response, firms have updated their websites, systems, and services to accommodate personal tastes and standards [2].

Personalized recommendations are getting popular throughout social media as well as e-commerce websites. Organizations can infer users' preferences by collecting their click data, thus harvesting users' attention for benefit. Especially with the advent of algorithms, the personalized recommendation system becomes powerful, sophisticated, and accurate compared to the past.

In the early 1990s, personalized recommendation systems were created to help users address information overload by using collaborative filtering [3]. And in today's age, social media such as Facebook, Instagram, YouTube, and TikTok are the main force in applying personalized recommendations to keep their users active and attract their attention [4]. Because of the openness of social media, everyone has the chance to post on the Internet, thus the volume of user-generated content keeps growing [5]. Information overload is exacerbated due to loads of information flooded over social media from users, organizations, and other institutions, which makes it even harder for users to make the right decision based on fully acknowledged information.

The personalized recommendation is one way to address this issue, the goal of which is to recommend the most suitable content based on users' characteristics and personal preferences [5]. Several studies have documented that personalized recommendation systems help reduce information overload by presenting organized choices and thus improve efficiency in terms of users' decision making [7], hence, increasing users' satisfaction. Additionally, the recommendation systems effectively present products and services to audiences and reduce the rate of advertisement avoidance [4]. However, this effect could be moderated by motivation, personal characteristics, situation, privacy concerns, etc. [9].

Several studies point out that the personalized recommendation system has some demerits and risks. Since the algorithm is the kernel of the recommendation system it involves users' data collection either explicitly or implicitly [10]. Because users' preferences are the basis of further inference and prediction, the more data collected, the more accurate the algorithm could be [11], privacy concerns [12] have therefore become one of the most unsettling risks of recommender systems. For example, the "unexplainable concerns" behind the "black box" of the algorithm and the "writer bias" within the algorithm have become hot social topics. The recommendation system greatly simplifies the process of finding satisfactory information, which may exacerbate cyber-balkanization [13]. Konstan and Riedl point out the main concern of cyber-balkanization is that it makes it more difficult for people to talk to each other, creating increasingly isolated sub-communities [3]. People could become lonelier and separated because of this isolation. Another concern for the personalized recommendation is that it may lead to homogeneous content because similar information keeps coming out in front of users who may get tired of absorbing it, which in contrast could cause a filter bobble effect and makes it even harder to accept things that they are not familiar with. According to [11], homogenization can not only cause the user to behave more similarly but also cause each user behaves more like its nearest neighbors because of the recommendation feedback loop, which could lead to the user experience loss in utility [15].

Most research about personalized recommendation systems currently focuses on the accuracy of algorithms, which is the core of the recommendation system. But accuracy is just part of the recommendation system and does not fully represent the users' satisfaction in terms of recommendation outcomes. [12] point out that if the system recommends the same items every time, users' satisfaction will decrease even if the recommendation system has a high accuracy rate [16]. [13] is a global measure of consumer attitudes and perceptions of online marketing. DSI measures the top four factors of digital satisfaction: trust, privacy, utility, and social, twice a year, tracking the level of importance and consumer satisfaction [17]. So, based on the above it is worth reflecting that do personalized recommendation significantly increases users' satisfaction? Why do some people tend to accept algorithmic recommendations while others resist them? In view of the fact that the analysis of users' attitudes and perceptions could provide useful public opinion reference for regulators from the demand side, the empirical analysis of users' tendency to accept algorithm recommendations and their satisfaction with social media is of practical significance.

This study examined the relationship between personalized recommendations and users' digital satisfaction from the user's perspective and explores the factors that influence user satisfaction through the four dimensions of digital satisfaction. In addition, we also integrate the personal characteristics of users to consider the recommendation system, thus filling the shortcomings of previous studies that primarily focus on accuracy instead of users' satisfaction and experience.

Based on the above, we propose the following research questions:

DOI: 10.54254/2753-7048/3/2022523

RQ1: What is the relationship between personalized recommendations and the digital satisfaction of users?

RQ2: What characteristics do people with a negative attitude toward personalized recommendations have?

2. Research Method

Survey research is a kind of social research method that adopts a self-administered questionnaire or structured interview to collect data systematically and directly from a sample taken from the whole and understand social phenomena and rule through statistical analysis of the data [18].

The advantages of the survey research are wide application range, high collection effective, scientific method, large sample size, and the results are highly representative. We adopt questionnaires because they can easily quantify people's digital satisfaction. So, it can help data analysis and make the research more scientific.

The survey instruments on which database archives are based are prepared by professional researchers, and the data collected are likely to have greater reliability and validity, as well as provide even greater flexibility for analysis [19]. The great flexibility can provide the possibility for abundant infer. A major problem in nearly all cases is obtaining a sufficiently large sample to enable a statistical analysis sufficiently powerful to draw conclusions about the target population. In contrast, several archival databases have thousands of cases representing random samples from a variety of large populations [20]. That improves the representation of the sample.

The data were collected through the Medill School of Northwestern University in 2021 in the U.S. The total sample is 1002 with a balanced gender ratio in data composition. After defining samples with preference values less than 4 as negative attitudes, our focused study sample size was 255, representing approximately 25.4% of the total.

The conceptualization is divided into two parts, which are also two basic variables involved in our research. Digital satisfaction was conceptualized into four constructs: utility, privacy, trust, and social community. A seven-point Likert scale was used to measure the general satisfaction of the online experience and the four components of digital satisfaction, the chart below shows our constructions. The answers to these questions were summed up to generate a new variable representing the average digital satisfaction, thus observing the overall satisfaction of users.

When it comes to the measurement of personalized recommendations, we collected data in terms of users' preference for personalized recommendations, number 1 represents the least likable for personalized recommendations which stands for negative attitude towards personalized recommendations, while number 7 represents the top preference for recommendations. Followed by 2 questions about measurements of information overload, which is an important motivation for people relies on recommendations. Then we surveyed the extent of helpfulness in terms of personalized recommendations, and to what extent users think personalized recommendations would be helpful and useful. The last part is users' dependency level on personalized recommendations.

Table 1: Four components of digital satisfaction.

Construct	Measurements
Trust	I am skeptical about anything I read online about $ {Q3a.selected.text}.
	I generally mistrust the information I get online about $ {Q3a.selected.text}.
Utility	The Internet is the most efficient means for me to get the information I need about $ {Q3a.selected.text}.
	When it comes to making decisions about changing $ {Q3a.selected.text}, I can complete tasks more easily online than offline.
	Being online helps me get things done when it comes to $ {Q3a.selected.text}.
Privacy	When I look up information about $ {Q3a.selected.text}, I find it creepy when websites know information about me that I have not directly communicated.
	When I look up information concerning $ {Q3a.selected.text}, I am concerned about my privacy online.
Social	In discussing $ {Q3a.selected.text}, I appreciate the glimpses into others' lives that I get online.
	When considering $ {Q3a.selected.text}, I love to connect with other people by going online.
	I use the Internet to engage in discussions with others about changing $ {Q3a.selected.text}.

Table 2: Four components of personalized recommendation.

Personalized Recommendation	
Preference	I appreciate receiving personalized recommendations based on my past online behavior.
	I wish the information I receive online was better prioritized based on my preferences.
Information overloaded	I find the amount of information online to be manageable.
	I am frequently overwhelmed by the number of choices and options online.
Helpfulness	I find online recommendations and reviews provided by others to be helpful.
Dependency level	I rely on customer ratings that I find online to make decisions.

3. Research Result

To answer RQ1 about relationships between personalized recommendation and digital satisfaction, we conducted a Pearson correlation. The result showed that the value of the Pearson index was 0.481, which means that there is a strong correlation between digital satisfaction and attitude towards

DOI: 10.54254/2753-7048/3/2022523

personalized recommendations (Table 3). Correlation is significant at the 0.01 level(2-tailed). To answer RQ1 more clearly, scatter plots were used to show the correlation virtually. Figure 1 shows that digital satisfaction is positively and significantly correlated with attitudes towards the personalized recommendations, and the liner fit result is y=3.8+0.78*x.

This paper also conducted one-sample t-tests to compare the means of four dimensions of digital satisfaction between people who do not like personalized recommendations and the overall samples. The result showed that the values of trust, utility, privacy and social were significantly different between people who do not like personalized recommendations and the overall. In conjunction with Table 4, the mean values of trust (M1=3.7619), utility (M1=4.1759), privacy (M1=4.0992), and social (M1=3.4987) are much lower than average respectively. Specifically, the value of the trust (t[251]=-6.268, p<.001), utility (t[251]=-7.708, p<.001), privacy (t[251]=-4.628, p<.001), and social (t[251]=-10.851, p<.001), indicating that people who do not like personalized recommendations significantly tend to have a lower trust on digital information, they have more dissatisfaction of privacy and online social community. Additionally, they are less likely to obtain the useful information they want.

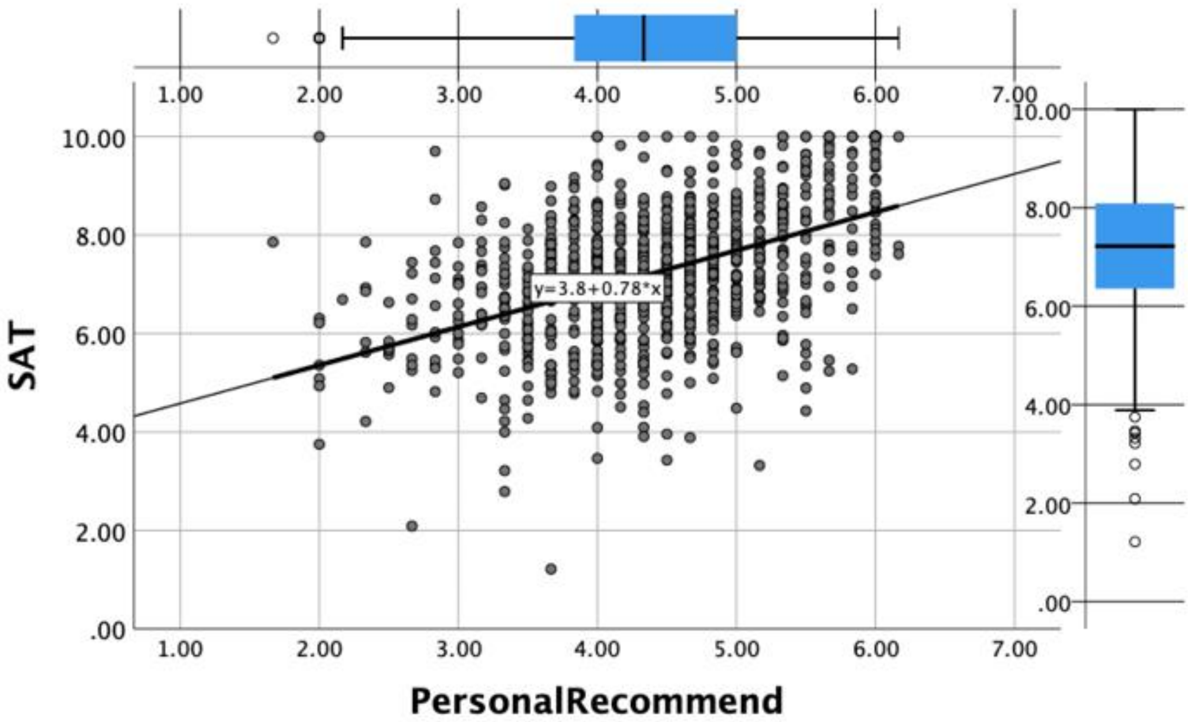

Figure 1: The correlation between digital satisfaction and attitude towards personalized recommendations.

DOI: 10.54254/2753-7048/3/2022523

Table 3: Correlation between digital satisfaction and personalized recommendations.

Pearson correlation			
		Digital Satisfaction	Personalized Recommendation
Digital satisfaction	Pearson Correlation	1	.481**
	Sig. (2-tailed)		.000
	N	980	980
Personalized recommendation	Pearson Correlation	.481**	1
	Sig. (2-tailed)	.000	
	N	980	1002
**. Correlation is significant at the 0.01 level (2-tailed).			

P=0.481<0.05 Therefore, there is 95% confidence that personalized recommendation has a positive correlation with digital satisfaction.

Table 4: One-sample t-tests compare four dimensions of digital satisfaction.

One-sample t-test				
	t	df	Sig. (2-tailed)	Mean Difference
Trust	-6.268	251	.000	-.51510
Utility	-7.708	251	.000	-.68187
Privacy	-4.628	251	.000	-.44109
Social	-10.851	251	.000	-.99522

Table 4 above illustrates the four dimensions of digital satisfaction, a one-sample t-test was conducted to test the difference between people with a negative attitude toward personalized recommendations versus the overall sample. The results show that they have significantly lower values (P=0.00<0.05) in terms of the trust, utility, privacy, and social community in the t-test than the overall.

Table 5: The characteristics of people with a negative attitude toward personalized recommendations.

One-sample t-test				
	t	df	Sig. (2-tailed)	Mean Difference
Age	6.341	254	.000	.623
Online hours	-4.180	254	.000	-1.212
Computer skill level	-2.502	254	.013	-.119
Information overload	-8.516	254	.000	-.58511
Political ideology	2.553	254	.011	.276

Table 5 shows five significantly different characteristics of people holding negative attitudes toward personalized recommendations in age, online hours, computer skill level, information overload, and political tendency.

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Table 6: Sources of digital information of people with negative attitudes towards personal recommendations.

Most helpful sources of digital information			
Sources	Frequency	Percent	Overall Percent
Social Networking Platforms (e.g., Facebook)	83	32.5	54.2
Job-related networking Platforms (e.g., LinkedIn)	23	9.0	14.3
Entertainment networking sites (Instagram, TikTok)	39	15.3	27.5
Blogs	18	7.1	11.3
Message boards (e.g., reddit)	30	11.8	15.6
Mainstream online media	83	32.5	30.9
Online Newsletters	34	13.3	11.5
Others	51	20.0	9.5

To answer RQ2 about characteristics of people with a negative attitude toward personalized recommendations, we conducted a one-sample t-test. People with negative attitudes towards personalized recommendations tend to be older in terms of age ($t[254] = 6.341$, $p < .05$), and their political ideology ($t[254] = 2.553$, $p < .05$) is significantly more conservative. It was reported that their online hours ($t[254] = -4.180$, $p < .05$) and computer skill level ($t[254] = -2.502$, $p < .05$) are dramatically lower than average. Notably, people who hold a negative belief in personalized recommendations are confronted with less information overload ($t[254] = -8.516$, $p < .05$).

According to the frequency distribution in Table 6, for people with negative attitudes toward personalized recommendations, the top three sources in terms of digital information are social networking platforms (32.5%), mainstream online media (32.5%), and entertainment networking sites (15.3%), which are consistent with the overall sample. It is worth noting that negative attitudes holders reckon mainstream online media (32.5%) and online newsletters (13.3%) more helpful when compared with the overall sample.

To sum up, a significant correlation between attitudes toward personalized recommendation and digital satisfaction was verified by the data and the Pearson correlation. As for the profile of users, several different traits were found that people holding negative attitudes toward personalized recommendations are mostly the seniors with lower online involvement, computer skill level, and more conservative political tendency. They do not have much pressure from information overload but have no faith in trust, utility, privacy, and social community online in terms of digital satisfaction. However, their media exposure habits are still dominated by social media and online news media.

4. Discussion

According to the data analysis results, a positive correlation is detected that people who hold a positive belief in personalized recommendations tend to have a higher level of digital satisfaction when compared to people who have a negative attitude towards personalized recommendations. So, why does this happen? And why people who are not interested in personalized recommendations are likely to have a more negative report in terms of digital satisfaction?

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4.1. Inaccuracy of Recommendation Affects Digital Satisfaction

It is widely known that the algorithm of personalized recommendation depends on the collection of user information, based on which, the platforms carry out content focused on users' preferences to meet the users' access to the content they are interested in and concerned about. They collect all clicks users make and all sites users skip or stay to analyze their preference for content and product. However, this could also mean that people who spend less time and energy online, such as older people, could be neglected by this well-designed algorithm recommendation system because of the lack of information. And this has been proved in our previous results. According to the data analysis, people who hold negative attitudes towards personalized recommendations reported spending less time online with a low level of computer use. Therefore, the algorithm recommendation system is not able to collect enough personal information to serve them accurate content catering to their preferences. A vicious circle is formed based on the mechanism of the algorithm system: People who do not spend much time online might receive incorrect recommendations that mismatch their preferences, which exacerbates their unwillingness to go online. This whole system initially designed to serve people with interesting content might end up upsetting their users and accelerating their escape, making platforms more difficult to draw user portraits and harder to handle their preferences. When it comes to the marketing which is driven by the content or direct product push, the personalized recommendation system needs to screen the product push according to the user's consumption habits, consumption fields, consumption levels, and other comprehensive information. Thus, it can segment the user market and enable businesses and users to obtain a more satisfactory online experience.

4.2. Less Information Overload Diminish the Urge of Using Personalized Recommendation

Because of the low frequency of internet use, users have no expectations of what personalized services are capable to do, they do not have the urge to explore how it works. Data analysis shows that people who reported themselves as having low digital satisfaction consistently have a low computer skill level, based on which, users might have a resistant and exclusive attitude towards things they are unfamiliar with. There is a shred of evidence showing that usage is positively correlated to information overload, which is the initial motivation to embrace personalized recommendations, otherwise, personalized recommendations do not need to exist. However, people who spend less time online might not confront with information overload, in this case, they lack the urge for personalized recommendations to help them solve information overload.

4.3. Personalized Recommendations have Some Insurmountable Drawbacks

One of the benefits of personalized recommendation in terms of utility is that it can alleviate user fatigue caused by information overload to a great extent. Information overload means users are given more information than they can handle within a given time frame [10]. According to the principle of least effort, when personalized recommendations can recommend high-quality, accurate content that can meet the search needs of users, it can greatly improve users' Internet efficiency and reduce the fatigue caused by their continuous search and decision-making. When users rely too much on personalized recommendations, there will be a new problem, which is content homogenization. Content homogenization is a problem caused by the "filter bubble", which makes the information available to users monotonous. Over time, users would be bored and lose interest in the fields they are originally interested in, then they would become eager to know more diverse information. But there is no quick and effective way to change this situation because most of the platforms are not available for having the option to turn off personalized recommendations.

The benefits of personalized recommendations in privacy are not obvious, but more is the crisis of privacy trust caused by its excessive control over the content. Because the system will not only use the personal information filled in by the user, but also collect and analyze the user's online behavior, deduce the real image behind the network through these behaviors, and predict what the users are thinking, what they will think, what are their potential need, etc. The phenomenon of "the personalized recommendation system knows me too well" will often lead to people's suspicion and fear. For example, people would think, "is my information protected?" "Will the system calculate any important information about me?" "If the website is attacked, will my information be safe?". The user involvement theory implies that users prefer content recommended by a process in which they have explicit involvement [10]. Therefore, trying to increase the interaction between users and the system, add little sweet tips, and allow users to manipulate the degree they want to be understood by themselves may reduce users' concerns about privacy issues. In some cases, the perceived quality of personalization may exceed the impact of privacy issues [23]. Therefore, if the system wants to reduce the factors that reduce user satisfaction and improve the recommendation quality without changing the collection of user information, it is a good approach to solve this problem.

Trust refers to the degree of trust in the content of network information. For those who often contact the Internet, the personalized recommendation may improve their trust in online information. The reason is that the system may have been able to provide them with accurate content. The more they see and know about the content in the field of interest, the easier it is to believe the information they see and form their judgment. If this judgment is captured by the system, it will push them to the judgment that meets their expectations and increase their sense of trust. Those who don't have regular access to the Internet, don't like personalized recommendations, and their trust in digital information is often low.

The advantage of personalized recommendation in the social community is that it could quickly and effectively find the groups users want to join, while the disadvantage is also obvious for increasing the cyber-balkanization. Several studies have reached a consensus that cyber-balkanization will create isolated sub-communities, exacerbating the isolation. For the elderly, it is a very important way to eliminate isolation through the Internet, but in fact, the loneliness generated by the social community could not solve their needs at all. In another case, because they do not have proficient computer skills, rarely contact the network to update their data, and lack exploration of the operation mechanism of the website, they are not capable to find a suitable community in the initial stage. So, it's natural they lose interest in the social community.

4.4. Generation X has been Neglected by the Personalized Recommendation System

While personalized recommendations have become an important tool for consumer insights in news production, video media, and shopping websites, and have improved consumer digital satisfaction to some extent, there is a group of people who have been overlooked by this system: Generation X, who born in the baby boomers are not native to the Internet and unfamiliar with the Internet. Their less digital involvement and experience make the algorithm recommendations for them is inaccurate and not well suited to their interests and concerns, so they rely less on social media, which gradually becomes a vicious circle that makes seniors increasingly marginalized on the Internet, which we call digital exclusion, which causes them emotional detachment and increases their loneliness, especially during the pandemic.

Seniors have long been overlooked by marketing and advertising too, rarely appearing in marketing campaigns unless they are involved in the medical or health field, and the stereotype is further reinforced by the fact that seniors in advertising are often portrayed in a way that makes them less clever and mobile. However, the Baby Boomers are the largest generation in the U.S. so far. Incredibly, they are made up of a generation of nearly 75 million people that many marketers have ignored, which seems like a total waste.

The U.S. Census Bureau [24] has pegged 2035 as the year older adults will outnumber children for the first time in U.S. history. By 2060 in China, one in three people–or 487 million–will be over 60. And yet by 2020, the world will have more 55-year-olds than 5-year-olds, and older people are expected to generate half of all urban consumption growth between 2015 and 2030. Not only are people living longer, but they are healthier than any previous generation of older consumers. What's more, they are also wealthier, driven by the expansion of Social Security and saving for retirement. Consumers over 50 own 80% of all bank and savings and loan deposits and report $2.4 trillion in income, which represents 42% of after-tax income in the U.S. HBR presents evidence that 50% of everything sold at retail (both in-store and online) is sold to people over 50. According to a Pew Research Center report [25], 68 millions of them will still be with us by 2028, which means that we must get closer to this audience that has huge economic potential. How to get marketing close to generation X is a valuable and rewarding question.

5. Conclusion

This article has reviewed the development process of personalized recommendations and then pointed out several advantages bringing to life and potential threats that could have an impact on users' digital satisfaction in terms of the trust, privacy, utility, and social. By analyzing the data set DSI_2021, our research questions were answered. While in the era of social media, everyone seems to enjoy the convenience of customized and personalized recommendations based on algorithms for reducing their information overload, we found that there are people who do not like personalized recommendations, and the attitude toward personalized recommendations is positively correlated to users' digital satisfaction (P=0.481**), which means that people who hold a negative belief about personalized recommendations tend to have low digital satisfaction in terms of their online experience. Even though people who do not like personalized recommendations are only about 25.4% of the overall percentage, that does not mean we can ignore them, especially when they are the relatively wealthy and potential group of consumers in the United States. Therefore, we explored more deeply the reasons that could explain this correlation. As data shows that people who have no faith in personalized recommendations reported being senior in age, less time online, lower computer skill levels, and more conservative about politics. Simply put, they are generation x, who have always been neglected by advertisements and marketers for a long time while they are full of potential to consume for possessing over 50% of the wealth in America with more savings and more leisure time. However, nowadays more and more product advertisements and campaigns are moving online which leverage personalized recommendations to leave an impression, encourage interaction, and promote sales. With the absence of such a huge market, we should think about how to increase the internet usage and marketing engagement of generation x, thus breaking the vicious circle of dissatisfaction caused by inaccurate personalized recommendations.

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