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Alleviating Information Cocoons and Fatigue with Serendipity: Effect of Relevant Diversification and its Timing

Shuyi Fang
Xi'an Jiaotong University, shuyifang2-c@my.cityu.edu.hk

David (Jingjun) Xu
City University of Hong Kong, davidxu@cityu.edu.hk

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Short Paper

Shuyi Fang
School of Management
Xi'an Jiaotong University
Xi'an, China
Department of Information Systems
City University of Hong Kong
Hong Kong, China
shuyifang2-c@my.cityu.edu.hk

David (Jingjun) Xu
Department of Information Systems
City University of Hong Kong
Hong Kong, China
davidxu@cityu.edu.hk

Abstract

With the rapid development of online media, in which personalized recommendations are provided, users are gaining increasingly narrow access to information, trapping them in so-called "information cocoons." At the same time, the increase in homogenized content has brought boredom and fatigue, which are not conducive to the long-term interests of a platform. Grounded in the entertainment consumption context, as represented by the Tik Tok short video platform, this study focuses on the information cocoon reinforcement and browsing fatigue phenomena caused by the lack of proper diversification. Then, to mitigate these issues, this paper proposes relevant diversified content and diversification timing countermeasures to optimize the "what" and "when" technical designs. We explore the role of perceived serendipity as a key path toward user diversity acceptance and browsing duration, thus alleviating the phenomenon of information cocoons and browsing fatigue and facilitating the common development of platforms and users.

Keywords: Recommendation, Diversification, Serendipity, Information cocoons

Introduction

Online media platforms rely on algorithmic technology to conduct personalized information according to user behaviors. However, according to recent surveys, users are discontented with such personalization. Based on a survey of 1,144 respondents conducted by the Social Survey Center of China Youth Daily in March 2022, 53.8% of respondents said they were not satisfied with personalization and preferred to turn off the recommendation function. Some users also stated that they prioritized turning off recommendations in entertainment apps, as this enabled them to see more types of content with greater randomness. Information consumption is a process of constantly seeking novelty and knowledge (Clarkson et al. 2013), a single and homogeneous recommendation contracts reality's unfixed and diversified demands. Given that personalization recommends similar content according to user preferences, it may gradually erode users' interest and lead to mental fatigue in information acquisition (Kaminskas and Bridge 2016). As users' "bored" feelings increase and satisfaction decreases, their engagement and usage time decrease, leading to the loss of user stickiness, which ultimately harms the interests of platforms over time (Song et al. 2019).

From the users' perspective, when recommendations become increasingly dull and repetitive, they might worry that the algorithms could build a "separation wall" of information and opinions while collecting user behavior data to build an object interest model. This narrows down their access to information and further traps them in a routine and paradigmatic environment of "information cocoons." Impeding the interaction of diversified opinions results in limited vision, extreme thinking, and other negative impacts (Helberger et al. 2018; Sunstein 2006). In other words, the lack of diversified information acquisition is the objective reason for the existence of information cocoons. While many academic debates have confirmed information cocoons, it lacks a causal relationship with personalization. In particular, effectively assuaging cocoons through the recommendation mechanism remains unexplored, and the simplified alternative quantitative methods have certain limitations in terms of realistic context, which still needs investigation to alleviate this dilemma from the nature of cocoon formation.

Motivated by these gaps in understanding, we build on Sunstein's original definition of information cocoons as the theoretical foundation, which is essentially derived from selective exposure psychology (Sunstein 2001). The result of selective exposure is a reinforcement of the original concept (Frey 1986; Kitchens et al. 2020), while the lack of diversity of personalized recommendations reinforces cocoons. We propose that relevant diversity recommendations can help enhance users' diversity acceptance and browsing duration; meanwhile, this proposed positive effect can be moderated by the timing of diversifications. That is, we explore the two factors (relevant diversification to user preference and diversification timing) related to the serendipity-oriented recommendation. Hence, how to recommend diversified information that attracts users to "choose" is the key to alleviating this problem. We refer to Ziarani et al. (2021)'s concept of serendipity, theorizing the underlying mechanism of perceived serendipity in assuaging information cocoon reinforcement and browsing fatigue phenomena. However, researchers have rarely investigated the positive effects of serendipity on other online social scenarios. In the case of product search, consumers typically choose only one of several products on a given occasion. Yet, a user is rarely "done" after browsing a short video, and such a noteworthy difference between the two contexts presents an opportunity for improving serendipity. Due to the highly concentrated and conflicting nature of political views, the phenomena of polarization and information cocoons are particularly obvious under the recommendation of political news. While how algorithms intensify cocoons in the entertainment personalization context and the role of serendipity in this process have been widely ignored in the literature. Hence, to alleviate information cocoons and browsing fatigue, we combine objective data and subjective questionnaire measurements as we explore the effects of relevant diversifications and the timing by which to recommend matters on user's acceptance in the context of the current trend of short video platforms (e.g., Tik Tok). This study aims to optimize the technical design for solving the "what" and "when" of diversified content recommendations to facilitate the common development of platform merchants and users, analyzing which of the three dimensions of serendipity plays an important role in the entertainment context of short video platforms.

Literature Review

Understand mental fatigue and information cocoons

Technological algorithms have gradually improved the ability to filter what consumers read, see, and hear. In addition, according to selective exposure theory, individuals prefer information that strongly agrees with or reinforces their own views and tends to browse content that fits their own preferences (Stroud 2010). Based on this attribute, once users are engaged, algorithms may filter out varying information and further limit exposure to a narrower range of content, leading to information homogenization that compounds the problem of being trapped in information cocoons (Pariser 2011). Some researchers have suggested that the reduced diversity of information may exacerbate the adoption of more extreme views (Helberger et al. 2018; Sunstein 2006). When people are unable to hear the voices of the outside world, this can lead to more personal prejudice and polarized social groups (Kitchens et al. 2020). Some studies have analyzed the phenomenon of extreme opinions caused by information cocoons in text reading, especially political views that are most prone to partisan tendencies (Sindermann et al. 2020); Kriplean et al. (2012) argued that reflective public thoughts should be encouraged; Nagulendra and Vassileva (2014) proposed interactive visualizations designed to improve understanding of information cocoon. Several studies have also examined the performance of different user attributes on information cocoon restrictions (Xu et al. 2020). This limitation is particularly prominent in the Tik Tok platform, where some users are addicted to the personalized space and spend a great deal of time in their subscriptions and discussion groups, which can further result in "more automatic" usage, worthless information acquisition and information fragmentation will restrict the development of their thoughts and narrow the scope of the knowledge they can obtain.

In some cases, the natural human instinct to seek information may involve a relatively unfocused sense of inquiry, whose initial goal is not to find some particular answer or fill some reasonably expected information gap (Miksa et al. 1992). Therefore, accurate personalization is likely to bring homogenous content, thereby leading to mental fatigue and humdrum (Akiyama et al. 2010). This not only hurts the immediate and long-term revenues of merchants on the platform (Song et al. 2019), but also raises concerns about being trapped in information cocoons. Bozdag et al. (2015) believed that by enhancing diversified recommendation tools, information homogeneity can be alleviated and breaks cocoons to a certain extent. When browsing entertainment social media such as Tik Tok, this kind of fatigue needs to be mitigated by diversity to avoid being caught in cocoons while protecting the platform from the loss of profits caused by users' boredom.

The "beyond accuracy" goal of recommendation systems - perceived serendipity

The information cocoons are caused by individuals who are more likely to interact with consensus views (Kitchens et al. 2020), which may reduce exposure to and consumption of diverse content, showing a relatively closed state. To ease the cocoons and fatigue which can meet the various information needs of users in their respective natural environments, some recommendation systems (RSs) begin to consider providing novel, relevant and unexpected recommendations (Kotkov et al. 2016; Ziarani et al. 2021), aiming to achieve serendipitous beyond the traditional accuracy goal (Bhatt et al. 2018; Niu et al. 2018). Previous research has shown plenty of approaches to generating serendipitous recommendations and summarized them into three categories (Kotkov et al. 2016): collaborative filtering (Afridi 2018), content-based filtering, and hybrid filtering. Ziarani et al. (2021) added context-awareness filtering on this basis. While several scholars have described how serendipities can be made in information RSs, especially in browsing, they focus more on the optimization and technical design of algorithms, while ignoring the interaction perception role of serendipitous and user. For instance, the SeqSense video system (Bhatt et al. 2018) provides less redundant as well as relevant recommendations.

The above information search highlights the importance of serendipity and its place in the field of information delivery. It is widely believed that serendipity is an opportunity to discover valuable things by chance, which helps users get interesting experiences, makes the recommendation system richer and more interesting, and greatly improves the information constraints brought about by accurate personalization (Fan et al. 2012). Some researchers consider serendipity has two components: surprise and relevance (Kaminskas and Bridge 2016; Yi et al. 2017). Their definition implies that even items known to the user are serendipitous. However, items that users are familiar with also have the potential to be unexpected, and these will not bring the user's surprise and attention (Ge et al. 2010). Thus, we adopt a more general and comprehensive definition of serendipity by including the novelty dimension (Ziarani et al. 2021). And serendipity refers to contents that are considered novel, unexpected, and useful to the user (Ge et al. 2010).

Diversified content and presentation timing

Once recommendations are generated, the next step in the "delivering recommendations" process is to present those recommendations to the user. Therefore, the focus of RSs includes designing "what" topics to recommend and "when" to present them. Previous studies have shown that recommending relevant content, which is likely to meet their information needs with positive utility (Song et al. 2019). Akiyama et al. (2010) suggested a serendipitous recommendation method using the distance and unexpectedness of items. The lower tendency of term co-occurrence, the higher unexpectedness is. Besides, Chiu et al. (2011) argued that increasing the diversity of recommendations can appropriately avoid situations wherein users are already receiving relevant information from other sources. Some researchers believe that it may be more beneficial to treat diversity and relevance together (Wu et al. 2018). These previous studies have proposed many approaches to enhance recommendation diversity, such as the Wundt Curve simulation (Gravino et al. 2019), dissimilarity calculation (de Bello et al. 2013), bandit approach (Lacerda 2015), and so on. Despite increased research in recent years, empirical studies are rare (Kotkov et al. 2016; Ziarani et al. 2021) and little consideration has been given to the psychological mechanism of how diverse content recommendations can trigger perceived serendipity.

In addition, the existing metrics do not consider "when to diversify" attributes on serendipitous, such as the timing of diversity, or rate of the presentation. A major goal of RS interface design is to persuade users to accept recommendations by facilitating their decision-making process (Li and Karahanna 2015). If users do not think these recommendations are "good" content to adopt, then they will not facilitate the process.

In the existing literature, a few studies have investigated the recommendation timing of users in the process of using the system and their choices (Tam and Ho 2005). Based on the theory of consumer search, Ho et al. (2011) further analyzed the different timing influences on users' acceptance, showing that the probability of users considering and accepting a given recommendation decreases when the timing of recommendation is delayed. However, our research is designed to help identify potential links and essential differences, as well as to provide basic recommendations for recommending content and timing for diversity.

Research model and hypotheses

Based on the entertainment consumption background represented by the Tik Tok short video platform, we explored the effects of relevant diversification on user preferences and the impact of diversification timing setting on alleviating the information cocoon reinforcement and browsing fatigue phenomena. Then, we conducted a theoretical derivation of the potential mechanism of perceived serendipity. As mentioned above, only focusing on personalized profiles has resulted in the lack of recommendation diversity and the emergence of information cocoons due to user selective exposure. Meanwhile, users' browsing fatigue will intuitively reduce the duration of their engagement. Therefore, the dependent variables of this study focus on the objective data of user diversity acceptance and total browsing duration, as well as on the subjective questionnaire of information cocoons and browsing fatigue. We will conduct a lab experiment to test relevant diversification (H1) in different diversification timing scenarios (H2), as shown in Figure 1.

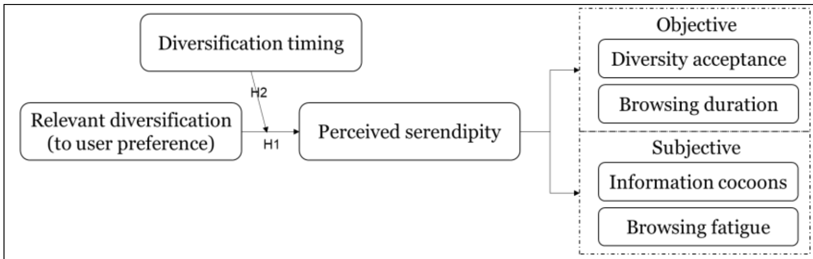

Figure 1. The Proposed Conceptual Model

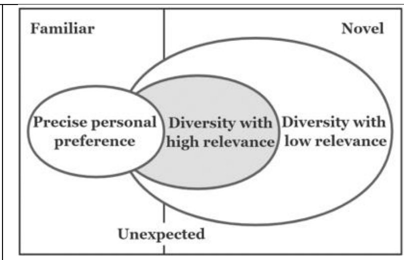

Figure 2. Venn diagram

Relevant diversification catering to user preferences

The definition of diversification is the act of introducing content that differs from those indicated by users' preferences (Kotkov et al. 2016). Through access to a wide range of information, users can obtain interesting experiences and release information constraints (Fan et al. 2012). To improve users' interest, we focus on the distance between diversified content and users' initial preferences. Perceived serendipity is an opportunity to find something valuable by chance. In turn, this encourages them to continue browsing the platform. Although diversity is highly different from serendipities, there is a relationship between the two concepts: providing users with diverse content can promote serendipity. However, serendipity involves novelty, usefulness, and unexpectedness, and only when all conditions are met can serendipity be perceived by users. According to information processing theory, consumers' demand for information is determined by the degree of perceived relevance (Wyer 2019). Given that content relevance is a relatively abstract concept, we visualize the distinctions between categories as geometric distances in a Venn diagram.

We took the intersection of familiar, novel, and relevant items that users perceived at a given time as described by Kotkov et al. (2016). "Familiar" includes users' personal preferences and other parts that are not new but of no interest; "Novel" stands for unfamiliar items that are relevant or irrelevant to the target user. As shown in Figure 2 above, each ellipse represents a content classification, and the edge defines the information and topic contained. The non-overlapping part represents the difference between their respective categories. Therefore, when the area of the non-overlapped and the distance between them (i.e., diversification) increases, representing the difference in individual preferences, this indicates a decrease in the diversity relevance and vice versa. Low relevance (i.e., diverse content far from users' preferences) may improve their unexpectedness and novelty, but its usefulness is difficult to guarantee and it is not deemed attractive by users (Kaminskas and Bridge 2016). On the contrary, high relevance can maximize the fit with users' preferences and is more likely to produce usefulness, but at the same time may lose the acquisition of surprise and unexpectedness. To some extent, this balance may have a different emphasis on the perception of serendipity. For example, a user who has "tourism" preference may be interested in “outdoor sports”, which have a certain relevance but do not completely overlap. Meanwhile, “celebrity gossip” shows a lower relevance, and the user may not be interested and will not watch. In summary, we propose that:

Hypothesis 1: Compared to precise personalized recommendations, relevant diversification enhances users’ diversity acceptance and browsing duration by facilitating greater perceived serendipity.

Timing of recommendations for diversification

We further pay attention to the recommendation to optimize the video platform (i.e., the setting of the diversification timing attribute to recommend). In this way, we can solve the question of when to recommend diversified content and propose an optimization of the presentation interaction mechanism in order to affect users’ perceived serendipity and then enhance their browsing time, freeing them from the information cocoons. Previous studies have explored the performance of consumers' acceptance of personalization under different recommendation timing (Shi et al. 2013), and they divided the timing of recommendation into product considerations and product choice decisions based on consumers' two-stage decision-making theory; Ho et al. (2011) found that with the delay of the recommendation timing, the accuracy of personalization improved, but it would increase the cost of consumers' selection process. Oh et al. (2014) believes that the timing of TV show recommendations is critical during user online time. However, few studies have addressed the timing of diversification recommendation.

In our context, when users obtain personalization, the timing of diversified recommendations can affect their psychological perceptions, behaviors, and satisfaction. In the concept of “timing,” the key factor is not the actual time consumed by the clock itself, but how many personalized contents the system recommends to users when diversifications are made. In other words, we manipulate the different timing settings of diversified content to change the cumulative amount of personalized recommendations. This refers to the timeliness of a system’s diversified adjustment when users may have fatigue feelings and information limitations. When the user is no longer interested in watching personalized content, we assume that s/he has developed mental fatigue caused by trapping in information cocoons. Specifically, slow adjustment means that the system does not recognize and adjust to deal with users’ fatigue in time, i.e., more non-responsive personalized recommendations are made. Users may have grown fatigued and fallen into the cocoon of information homogeneity before receiving diversified content. Fast adjustment means that once a user has a non-responsive personalized recommendation that s/he is not interested in, the system will immediately recognize it and recommend diversified content to relieve his/her fatigue. Thus, we propose:

Hypothesis 2: Compared to fast and slow timing of diversification recommendations, medium diversification timing can increase users’ diversity acceptance and browsing duration, because it strengthens the effect of relevant diversification on perceived serendipity.

Methodology

To investigate the effect of diversified content recommendation on user browsing fatigue and information cocoons, a laboratory experiment with a 2 (relevance of diverse content: low relevance vs. high relevance) × 3 (diversification timing: slow, medium, and fast) between-subjects design will be implemented in testing our hypotheses. Further, we will have a control group “Group 7” with no diversification, i.e., only recommending content based on users’ precise personal preferences.

Overall design

Short video platform will be our study context. Given that most of the digital platforms introduce short videos, this context is more generalized and closer to people’s living habits. Since video incorporates multiple factors such as sound, images, and text, it has a greater amount of scenario-based characteristics. Changing any factor may set off user interest and bring serendipity. Compared with news platforms that cannot measure the user's reading speed, video duration can be standardized and unified, which can better capture the precise browsing patterns of users. We design an experimental RS to simulate a well-known short video social platform, which matches reality (e.g., Tik Tok), and can be used to entice participants to browse short videos to complete an experimental task. During the experiment, we only recommend one short video at a time, which will play when users click on it. If users want to switch from one video to the next, they can click the arrow button on the screen to view other recommendations. Each video should be about 30 seconds and last no more than a minute. According to the setting, the system selects and provides diversified recommendations to trigger users' perceived serendipity, shown in the middle of Figure 3.

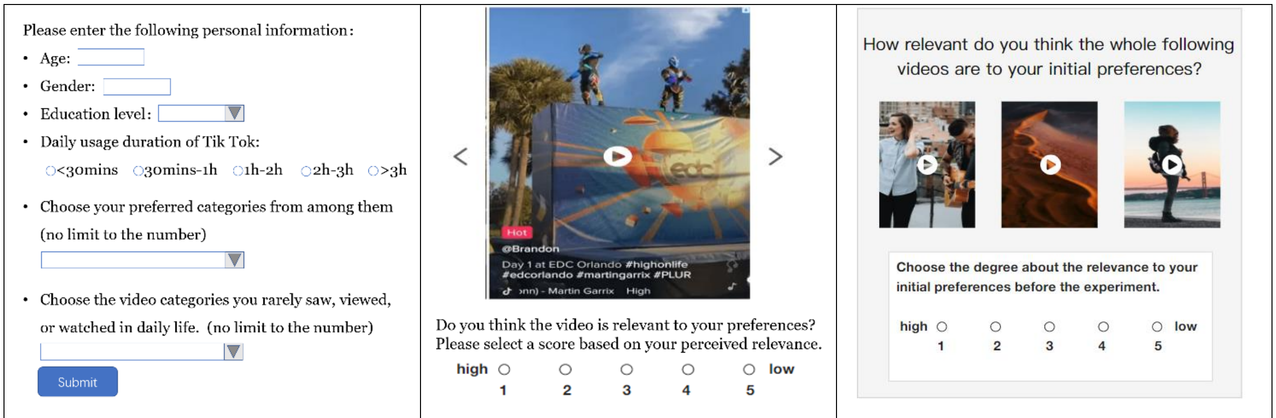

Figure 3. Illustration of the interface and relevance check

Videos with categorization labels are used in the content store, which contains 15 categories (e.g., sports, cooking, or travel, indicated as A-O), and each category stores 20 short videos. We will first recruit subjects to participate in the pilot test and collect their individual characteristics. The 15 categories will be ranked according to their preference, from most favorite to least interested, the data for which can be recorded as personalized preferences. Additionally, we will ask the subjects "What kinds of videos do you rarely watch in daily life" and choose their preferred video categories as preferences.

Since individual characteristics can affect mental fatigue and diversity acceptance, to improve the generalizability of this study, we consider control variables such as gender, age, education level (which may affect information acceptance), and daily Tik Tok browsing duration. We will also collect information about their demographic differences, cultural background, personalities (openness to information, introverted or extroverted, etc.), and social class (Xu et al. 2020) as control variables.

Manipulation of relevant diversification

The top 3 preferred categories selected by the subjects before the main experiment will be used to represent their personalized preference. According to the preferences score of each subject, the next five categories closest to the personalized preference score represent high relevance diversification to subjects' preferences, and the rest categories represent low relevance.

We will further conduct a manipulation check to ensure the reliability of our experimental design. Since some of the personalized recommendations or diverse recommendations have the potential to deviate from users' initial preferences as they browse, it is also important to confirm with participants how relevant they feel about these "personalized recommendations". We plan to ask participants after each recommendation how they feel about the relevance of the recommended item: "Do you think the video is relevant to your preferences? Please select a score based on your perceived relevance". At the end of the experiment, we will extract all the diversity recommendations from the browsing process and allow the subjects to rate how relevant these videos are to their preferences to further determine the relevant setting of each group. These are chosen before the experiment by asking the following question: "How relevant do you think the whole following videos are to your initial preferences?" The larger the number, the higher the relevance, as shown on the right side and middle of Figure 3.

Manipulation of diversification timing

In order to solve the negative impact of personalized recommendation, this experiment also studies the moderating effect of diversification timing. According to different timing manipulations, subjects are assigned to three groups of fast, medium and slow for short video viewing. Set π to the cumulative number of videos that the user chooses not to watch, which an user is not interested in this recommended video. When the user has accumulated π non-responsive (i.e., unclicked reaction) recommendations, the system will then expand a diversity recommendation from the high and low two kinds of relevant diversification categories. The setting of π is small means fast diversification. That is, once the subject is not interested in the recommended content, the RS will immediately conduct diversified moderating. After investigating subject's rank in the given 15 categories, assume that A, B, C are selected, which represent preferences, D, E, F, G, H are high relevance and I, J, K, L, M, N, O are low relevance. We show the main process in Figure 4. Use black square indicates a recommended category with personalization; blue square indicates a recommended category with diversity; "×" "√" indicates the subject's reaction; set non-responsive: π = {Slow. Medium. Fast} = after {8, 5, 2} negative reaction. The setting of timing means that when the number of non-responsive personalized videos accumulates to 8 (or 5, 2), the system will select a video from the relevant diversity categories to recommend. Then we continue to recommend the original personalized video and the above operation will repeat until the timing is reached again, until the end of the experiment. We will also consider diversification acceptance and browsing duration as dependent variables. We will conduct pilot tests to confirm the next 5 closest score categories to the personalized preference as high relevance, and the cumulative number, which is set to 8,5, or 2 could be considered as slow, medium, or fast adjustment.

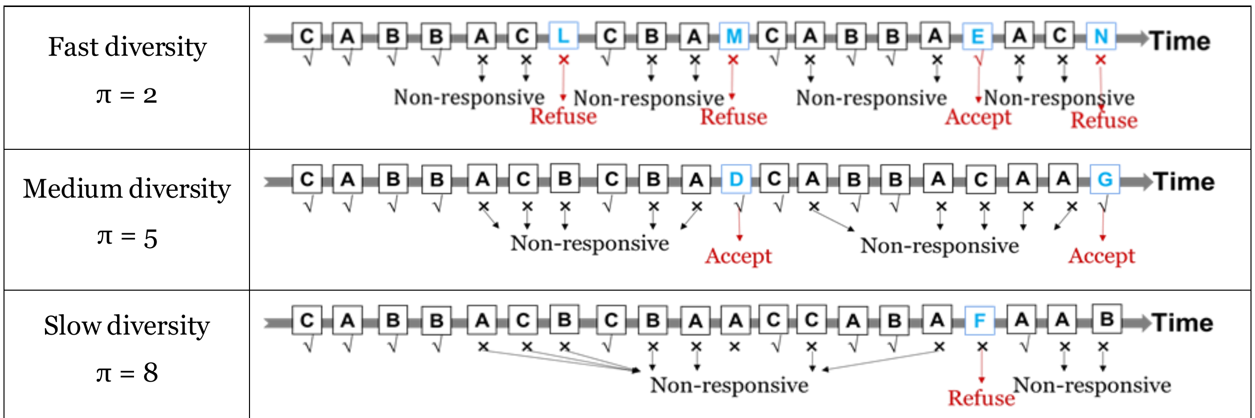

Figure 4. Manipulation of diversification timing

Measurement

Items for perceived serendipity of content recommended are adapted from Yi et al. (2017), which focus on the two characteristics of serendipitous findings, that is, useful and surprising, respectively representing the value to user demand preferences and the unexpectedness to users in this study. We further add the novelty dimension (Ziarani et al. 2021) in Table 1. This research aims to separate the three dimensions to examine which dimension has more weight in influencing serendipity.

Constructs	Measurement items	Sources
Usefulness	This video helped me discover some useful information.	Self-developed
Unexpectedness	The recommendation video I just saw was not planned for.	
Novelty	This video is new and unknown to me.	Ziarani et al. (2021)

Table 1. Measurement of serendipity and its dimensions

Diversity acceptance and browsing duration

In the setting of this study, we focus on the two dependent variables of user diversity acceptance and the overall browsing duration. This is because users' attitude of diversification will affect information cocoons brought by the recommendation system, and user browsing fatigue will directly affect their willingness to stay on the platform, representing information cocoon reinforcement and browsing fatigue phenomena, respectively. Furthermore, we set the ratio of the number of diversified recommendations clicked by subjects to the total number of diversified recommendations. Hence, "diversity acceptance" refers to the interaction between users and the system and their choice of whether to engage in the recommendation for browsing. Meanwhile, browsing duration emphasizes the intensity of user participation and measures the total actual watching time of each subject. Here, T is set as the ratio of the actual watching time divided by the total time of all videos pushed by the system. The higher the value of T is, the longer the duration of the usage (i.e., the greater the willingness to watch the recommended video). When the value of T is smaller, viewing time is shorter and the lower the likelihood that the video conforms to the subjects' preferences.

However, the timing operation may be contaminated by information overload. That is, browsing more personalized videos under "slow adjustment" may lead to fatigue and affect subjects' choice of diversity acceptance. Therefore, we will further measure the duration between two diversifications and capture whether users' interests change or not after browsing more homogeneous videos. Our aim is to disentangle the "fatigue" effect caused by the increased browse volume from the diversification timing effect and clarify which timing can better arouse users' interest in diversified content.

Discussion

This study contributes to the existing research in many ways. Theoretically, we enrich the examination of personalized recommendations. Previous studies have only considered the negative impact of the information homogeneity brought about by personalized algorithm filtering. In comparison, our study categorizes such impacts into information cocoons at the individual level and loss of user stickiness due to browsing fatigue on the platform level, thus introducing the mitigating effects of diverse content selection to fill this gap. Secondly, we use perceived serendipity as a key mechanism, which underlies the impact of relevant diversity on diversity acceptance and browsing duration. Third, although the previous literature has studied diversity goal in the context of personalized recommendation, few studies have considered when to diversify. Related to this, the current study creatively proposes the timing factor of diversification to enhance the understanding of alleviating the phenomenon of information cocoons and browsing fatigue. In practice, this study will have important guiding significance for network environment governance and short video recommendation system designs. This work will also provide practical guidance for policymakers and short video platforms so that they can take measures to broaden users' horizons, enrich their interests, and improve creativity. For short video platform merchants, how to design diverse content and recommendation mechanisms to meet the needs of users is a crucial survival issue. This study proposes a mechanism optimization method to provide a new way to improve user experience and meet user needs.

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