Reducing Information Overload in Recommender Systems

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Graphical Abstract

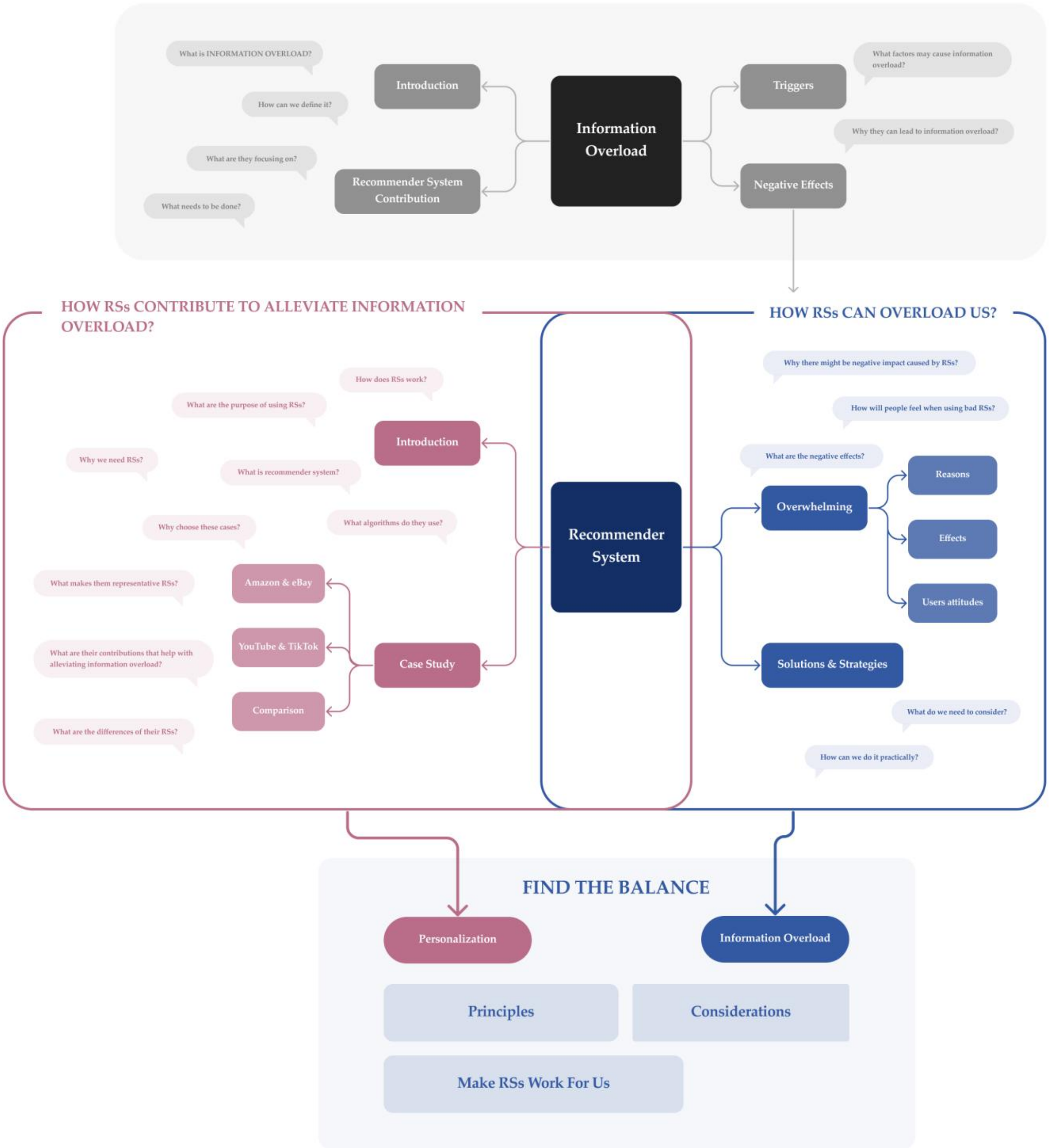

Figure 0 Graphical abstract

Abstract in English

In the era of digital flooding, recommender systems have become powerful tools to provide personalized recommendations to help people escape the digital deluge. This article examines the role of recommender systems and the challenge of information overload, exploring how recommender systems mitigate and exacerbate this dilemma.

This article first introduces the working process and summarizes algorithms of the recommender system, and then discusses the issues that people could have when confronted with a sea of information. It is important to understand the latest developments in recommender systems today. I choose four representative platforms for analysis: Amazon and eBay, YouTube and TikTok. These two groups of platforms demonstrate a variety of applications for recommender systems, from e-commerce to streaming services. I evaluate the recommender systems of each group and outline their technological efforts as well as the functional measures taken by their platforms to offer a more personalized user experience. After that, I concentrate on the issue of information overload, analyze the triggers that lead to the problem as well as how it affects people, and summarize the ways recommender systems have contributed to address it. We do not, however, avoid discussing the negative aspects of recommender systems; rather, we reveal any potential drawbacks and identify the reasons for them. The relentless pursuit of personalization can inadvertently lead to information overload. I examine these issues carefully and propose solutions based on good use cases and thinking.

Finally, I stress the significance of providing users greater control over their digital experience while maintaining a careful balance between personalization and overload. This work offers insightful information about the complexity of recommender systems and how they function in challenging situations of information overload.

Keywords: Information Overload, Recommender System, User Control, User Expereicnece

Abstract in Italiano

Nell'era dell'inondazione digitale, i sistemi di raccomandazione sono diventati strumenti potenti per fornire consigli personalizzati per aiutare le persone a sfuggire alla marea digitale. Questo articolo esamina il ruolo dei sistemi di raccomandazione e la sfida dell'eccesso di informazioni, esplorando come tali sistemi possano mitigare o esacerbare questo dilemma.

L'articolo introduce innanzitutto il processo di lavoro e riassume gli algoritmi del sistema di raccomandazione, per poi discutere le problematiche che le persone potrebbero affrontare di fronte a un'enormità di informazioni. È importante comprendere gli sviluppi più recenti dei sistemi di raccomandazione oggi. Scelgo quattro piattaforme rappresentative per l'analisi: Amazon ed eBay, YouTube e TikTok. Questi due gruppi di piattaforme mostrano una varietà di applicazioni per i sistemi di raccomandazione, dall'e-commerce ai servizi di streaming. Valuto i sistemi di raccomandazione di ciascun gruppo e ne delineo gli sforzi tecnologici, oltre alle misure funzionali adottate dalle loro piattaforme per offrire un'esperienza utente più personalizzata. Successivamente, mi concentro sul problema dell'eccesso di informazioni, analizzando i fattori che lo causano e come influisce sulle persone, e riassumo i modi in cui i sistemi di raccomandazione hanno contribuito ad affrontarlo. Non evitiamo, tuttavia, di discutere gli aspetti negativi dei sistemi di raccomandazione; piuttosto, riveliamo eventuali svantaggi e ne identifichiamo le ragioni. La continua ricerca della personalizzazione può involontariamente portare a un eccesso di informazioni. Esamino attentamente questi problemi e propongo soluzioni basate su casi di buon uso e riflessione.

Infine, sottolineo l'importanza di fornire agli utenti un maggiore controllo sulla loro esperienza digitale, mantenendo un equilibrio attento tra personalizzazione e sovraccarico. Questo lavoro offre informazioni interessanti sulla complessità dei sistemi di raccomandazione e su come essi funzionano in situazioni sfidanti di eccesso di informazioni.

Parole chiave: Sovraccarico di informazioni, Sistema di raccomandazione, Controllo dell'utente, Esperienza utente

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1. Introduction

In the digital era, recommender systems, or RS for short, are a key technological development that is transforming how people find and engage with content, goods, and services on various online platforms. The appearance of RS influences people's online experience significantly in multiple fields, including social media, e-commerce, video and music services, etc., which are closely related to people's daily lives. It gives great benefit to users in making their way through the deluge of options. Fundamentally, a recommender system is an algorithmic framework or intelligent software that records and collects user interactions, online behaviors, and preferences in a digital environment and then generates personalized recommendations. Nowadays, recommender systems have become essential instruments for improving user experience, interaction, and judgment by using sophisticated data analytics and machine learning methods.

Personalized accuracy is a crucial factor that could contribute to user engagement in RSs, which denotes their capacity to sift information and generate product recommendations according to the preferences of consumers. No matter if it's recommending an interesting book, an attractive movie, or a wonderful item, RSs benefit significantly to user experience improvement by providing carefully chosen options that meet individual interests and preferences.

With the pursuit of personalization, recommendation systems (RSs) have made notable progress. Aside from making recommendation algorithms better, a lot of attention is also paid to adding features for user-centered customization and creating tools that encourage openness and user control. These initiatives enable users to have more user control, which means they could actively influence the recommendations they receive before or after their online activities.

While RSs work to improve personalization, they are stepping into a more complex area. The emergence of the recommendation system could have helped reduce users' information overload problems with the huge amount of information on the Internet, but it may have caused a series of new problems. It is becoming more important to strike a good balance between user control, personalization, and the possible risks of information overload. When thinking about issues that may appear in the process of recommendation generation, there are usually concerns regarding diversity and serendipity because of the possibility that RSs could unintentionally lead users into "filter bubbles,", which means they only see content that confirms their preexisting opinions. Due to the complexity of managing the relationship between personalization and information overload, we need to

carefully consider the causes and possible impacts of this problem and propose solutions to minimize its negative effects.

2. Recommender System

2.1 Overview of Recommender System

A recommendation system is an intelligent tool that helps people make decisions in the ocean of information. It is popular in various fields and platforms in today's digital age. In general, the system predicts the rating of items according to the user's preferences and interests, which requires the use of their past online data. Research on recommender systems has lasted for more than twenty years, and several approaches have been developed and iterated through the years. In order to improve the user experience and promote user engagement, different platforms choose the algorithms that most suit their systems to provide users with the best recommendations. Besides, beyond algorithms, the presentation form of recommendations will also affect the user experience. Appropriate display methods and interface design can help improve users' happiness during their experience as well.

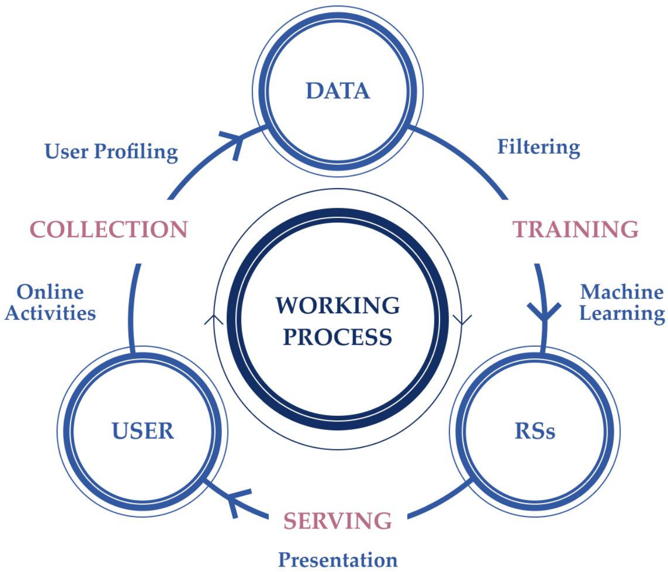

Figure 2.1 Recommender system working process

Fundamentally, recommendation engines involve the processing of data. Based on this, the working process of the recommendation system can be divided into the following three stages(Figure 2.1). Each of the various critical stages is essential to improving user experiences.

1. Data Collection and User Profiling

Recommendation systems essentially predict the ranking of undiscovered items. In order to complete this prediction, sufficient data needs to be gathered first. Data is crucial in a recommendation engine. During the data

processing, the more data are utilized in the model, the more effective the recommendation results will be (Roy 2022).

The recommendation system utilizes data from products and users. Product data mainly refers to product attributes, such as the genre of book, the type of movie, the style of clothing, etc. This type of data can usually be obtained in advance from the system's database, and the required data type can be extracted during application. The data from users is much more complicated. Due to the diversity and variability of platform users, user data is mainly divided into two categories. The first is the user's personal information, called user demographic data, such as age, location, gender, etc. This type of data will play a great role in classifying similar user groups during the analysis stage. The second one is user behavior data, which reflects users' online activities. Among them, the data obtained through user input is explicit data, such as search history and product comments. The other is more obscure. It is collected indirectly from the user's online interaction, for example, how long the user stays in a web page, how many products the user has viewed before completing a purchase. This type of data may be more complex to analyze, but sometimes more truly reflects user preferences.

Most recommendation systems collect data in both implicit and explicit methods, and the richness of data plays an important role in the accuracy of result prediction.

2. Recommendation Algorithms

After obtaining sufficient data and storing them in a suitable database, the system needs to analyze data. Developers can choose to apply a real-time system or batch analysis to analyze the data on a regular basis according to our needs. In order to acquire the data needed to provide recommendations to users, the recommendation engine also needs the best algorithm to filter the data, which is also one of the most important steps (Kaur 2019).

Personalized recommendation systems mainly consist of three approaches: Collaborative filtering , Content based filtering and Hybrid approach.

a. Collaborative Filtering

Collaborative filtering is currently the most widely used filtering technique. It collects users' behaviors and feedback, creates links between users with the same attributes and similar interest preferences, and will recommend the same type of items to users who like the same ones. The principle of the approach is the belief that users with preferences for the same products will have the same tastes now and in the future. This type of technique relies heavily on user experience to derive ratings rather than profiles of users and products to make recommendations, so the quality of its predictions will be higher, but at the same time, it requires a large amount of data, which may create a cold-start problem initially.

b. Content based Filtering

This type of recommender system generates recommendations after analyzing the features of the product and the user. It analyzes the attributes and characteristics of the product and compares them with the user's preferences. When the characteristics of the product are the same as the user's previous or current preferences, the system recommends it to the user. The advantage of this type of filtering technique is that it provides more transparency to the user about how the recommender system works, in addition to allowing lesser-known items to be recommended to the user. However, it still has some limitations, as it only focuses on the user's statistics data without utilizing the user's interaction data, and it is unable to collect feedback from the users on their satisfaction with the items.

c. Hybrid recommendation

Since both algorithms have their own advantages and disadvantages, hybrid approach utilizes both techniques to reduce their drawbacks. This approach requires more sophisticated technology but provides users with more accurate and diverse recommendations.

3. Presentation of Recommendations

Recommendation results are a series of items provided to the user, generally based on ratings derived from backend algorithms. (Bauer 2022, 38) In order to create seamless recommendations in the user's online experience, recommender systems often choose a variety of means for the user to be exposed to the recommendations. Apart from the static or dynamic display of recommendations in the form of text and images, horizontally or vertically on the web page, some platforms will also use more traditional email or SMS to give users personalized recommendations. The degree of acceptance of a recommendation to users has a lot to do with the user-trust building issue in the recommender system, and the form in which the recommendation is presented has a great impact on it (Pearl.P 2013). According to previous studies, the seven aspects of accuracy, familiarity, novelty, diversity, context compatibility, exploration of recommendations, and efficiency of information are the most important. The improvement of these seven aspects can effectively help users in their decision-making process. If the recommender system can successfully stimulate the trust and motivation of users, it will be more effective in increasing the favorability and engagement of users towards the system.

4. Facilitating User Experience and Mitigating Information Overload

In the rapidly developing digital era, people have access to great more information on internet, and the amount of information and the structure of information has great effect on the user's decision-making. The rise of recommender systems in recent years has played a crucial role in alleviating

the information overload problem. Recommender systems can ensure that the most information accessible to the user is closely related to the user's preferences, filter a large amount of irrelevant information in the flood. Recommender systems simplify users' process of discovering the desired product, and greatly save their time and energy (Lurie 2004).

2.2 Challenge of Too Much Information

In today's day and age, the flood of information has become one of the biggest challenges facing people.According to the statistics of Average Daily Time Spent using the internet by online users worldwide, between 2017 and 2023, people spent an average of more than 6.4 hours online. A report by the University of California-San Diego says that an average American could consume roughly 100,000 words heard or read per day, which is a pretty big number. In the digital age, the amount of information available to people is inevitably increasing, while the amount of information that people can effectively receive is limited. This makes it a challenge to get the information you want quickly in the flood of information.

One of the biggest challenges posed by too much information is cognitive overload. The human brain is limited in its ability to process information, and can generally only process a quantitative amount of information in a given amount of time. Once faced with too much information, people are likely to become stressed and confused. Attention span and cognitive performance may be adversely affected when people continuously view large amounts of information.

In social networks, where a large variety of information is mixed together, it is difficult to distinguish between the real and the fake. In order to recognize the information as real or not, people must keep a clear mind and think critically. However, not everyone has the ability to do so. In addition, there is a high probability that there will be some information bias in the transmission process. Even if it is a subtle difference, a small amount of information can add up to a large amount of bias. This can lead to the undesirable spread of misinformation and the loss of trust in social networks. The fermentation of public opinion is thus likely to make the Internet an avenue for spreading tension and anxiety, with unwanted emotional health effects.

On the other hand, in the age of big data, the exposure of too much information can also lead to privacy and security issues. When people surf the Internet, they may find that the same type of products they have searched for on one website will appear in the recommendation lists of other websites. While this brings convenience and surprise, due to the opaque nature of data sharing across different platforms, people start to worry about the security of

their personal information and its potential misuse. This type of concern can also lead to anxiety.

In short, the challenge of too much information is a common problem in the digital age, and it is closely related to our lives. We should not just enjoy the convenience of the variety of options, but also pay attention to the new concerns caused by the overload. We need to fully understand the causes of information overload on the Internet to build effective strategies, which is important to enhance the online experience of users and reduce the burden in the digital flood.

3. Case Study Analysis

3.1 Background

In recent years, more and more attention has been paid to recommendation systems, research on recommendation algorithms and the development of related technologies have continued to advance. Recommendation systems are gradually being used in more fields, including streaming service, e-commerce, social networks, tourism, healthcare and other fields, varied platforms that rely on recommendation systems have been developed (Ko 2022).

In the field of social networks, the system will suggest users who are most likely to become friends based on the user's friends or interests eventually; in the field of tourism, users can find the best route to a certain attraction with the help of the recommender system; in the field of health care, the recommender system can provide users with the best treatment plan based on their biological data. Among them, what makes streaming media and e-commerce different from these fields is that they usually provide users with a large number of choices from their huge content libraries. Users need to search for their goals in a variety of items or discover their preference in a large number of videos and songs. The offering diversity makes it easier for users to fall into the dilemma of selection and face information overload. In addition, in these two fields, users' active participation plays a crucial role in improving the personalization of recommendation results, the recommendation systems of both categories depend on users' continuous interaction with content for their business model.

In this chapter, I will conduct case studies on typical recommender systems in the fields of e-commerce and streaming media. As areas closely related to the daily lives of billions of users around the world, e-commerce and streaming media have a profound impact on users' behavior and decision-making. In recent years, there are many researches focusing on comparison and analysis of different recommendation algorithms. Here I will briefly summarize the differences in algorithms and data of recommender systems, focusing on the analysis and comparison of the interfaces in different platforms.

In the past few years, research related to e-commerce recommendation systems has increased year by year. There is a studies evaluated statistical data that can be used to confirm business. It have shown that the application of recommendation systems can bring more valuable users and annual revenue, and promote growth of business in the end (Ko 2022). Amazon's sales growth trend can also support this. According to statistics on the number of research articles on recommender systems in recent years, a large

number of studies on recommender systems in the e-commerse field appeared between 2013 and 2015. And from 2017 to 2020, Amazon's sales showed a significantly higher growth trend than in previous years. This can be inferred about the positive effect of recommender systems on companies business growth, which also shows that it is meaningful to conduct a comparative analysis of recommender systems in the e-commerce field. Here, I chose Amazon and eBay for case study. The difference between the two is that Amazon primarily sells products directly to users, while eBay sells with its auction-style listings and third-party sellers. Both platforms aim to enhance user shopping experience, but the difference is that Amazon emphasizes product recommendations and personalized shopping journeys, while eBay focuses on dynamic bidding and competitive pricing. The differences in the market models between the two make the analysis of the recommender systems of the two platforms more meaningful.

For streaming service, I chose YouTube and TikTok, two video platforms, for use case analysis. The number of users of these two video platforms has increased exponentially in recent years and they have extensive influence in the video field. On the other hand, the types of videos they provide are very different. YouTube is the platform providing long videos while TikTok representing short videos. Both platforms prioritize user engagement, but they do so in different ways. YouTube's recommendation strategy is designed to keep users on the platform for longer periods of time, while TikTok focuses on shorter and more engaging content. Therefore, explore the differences in recommendation strategies for long and short videos would be interesting.

3.2 Use Case Analysis

In this section, I will conduct a use case analysis of the recommendation systems of Amazon and eBay in the E-commerce field and Youtube and TikTok in the streaming service field. The analysis is done from the technical level and functional interface.

3.2.1 E-commerce Recommender System

In order to make the analysis of the recommendation system easier to understand, a scenario will be set in advance for each field to help understand the recommended content.

Assume a scenario: the user is about to use up the makeup remover she purchased from Amazon three months ago, and now she wants to repurchase a new one. She thinks the brand of makeup remover she used before is good enough, and she has the idea of repurchasing it. But at the same time, she

wants to see if there is a better choice. In addition, the user has an upcoming trip, she would like to buy a camera to take pictures while traveling. So far the user already has a preferred brand, but the price is a bit high for her. So she is still on the lookout, hoping to buy the product at the most suitable price. Now she is searching for the desired product on the platform.

1. Amazon

Amazon is an industry giant in the field of e-commerce and is the largest e-commerce brand in the world. It has over 197 million monthly active users of its app and has a total net sales revenue of $5,130 in 2022. Amazon is also known for its ability to come up with personalized recommendations for users. Some statistics show that 35% of Amazon's annual revenue comes from the recommendation engine it uses, which is all due to Amazon’s efforts over the years to improve its recommender system.

On a technical level, Amazon uses a variety of recommendation algorithms to help analyze and predict user preferences. Collaborative filtering is the foundation of Amazon's product recommendations, which collects, filters, and analyzes a user's purchase record and browsing history to surmise their needs. Among this, collaborative filtering algorithms can be subdivided into user-based collaborative filtering and item-to-item collaborative filtering. This algorithm relies on a large amount of user data, and their main purpose is to identify similarities between users and potential recommended products to users with similar preferences. Amazon also utilizes content-based filtering algorithms that analyze product categories, attributes, and features to recommend similar products to users. Natural Language Processing (NLP) is used to recognize keywords in other textual data as well, such as user reviews, to predict the user's preference for the product. Additionally, in the era of the rise of machine learning, Amazon's recommender system also utilizes machine learning and deep learning algorithms to push the recommender system forward in more complex data environments.

Recommendation function module customized for users

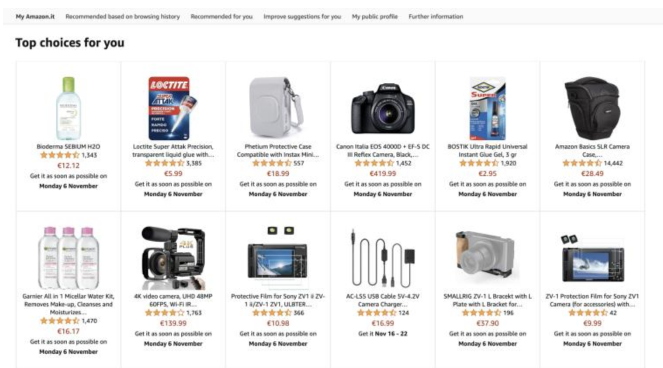

Figure 3.1 “Your Amazon.com” on Amazon

There is a special module in the Amazon platform called "Your Amazon.com"(Figure 3.1) for users to view the system's recommendations for themselves. Under this module, users view the product list generated by the system based on their past purchase records and access history data. This includes similar products of the same type that the user has purchased, products that have been viewed but not purchased, and other similar products. This function requires users to actively click on the menu to access it. It has high requirements on users' active participation with extra effort.

Real-time recommended product list

- Based on user's browsing history

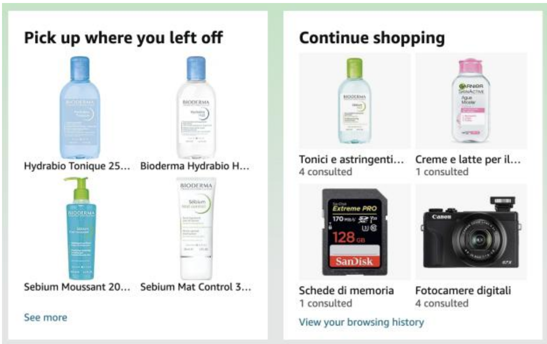

Figure 3.2 Modules for continued shopping

When users returns to the homepage, the first thing they see are two blocks, which display the user's browsing history(Figure 3.2). It is helpful to arouse the user's needs and promote the user's continued purchasing behavior.

Figure 3.3 Recommendations based on search history

A list of similar products will also be displayed at the bottom of the user's browsing history page(Figure 3.3).

- **Based on product categories and attributes**

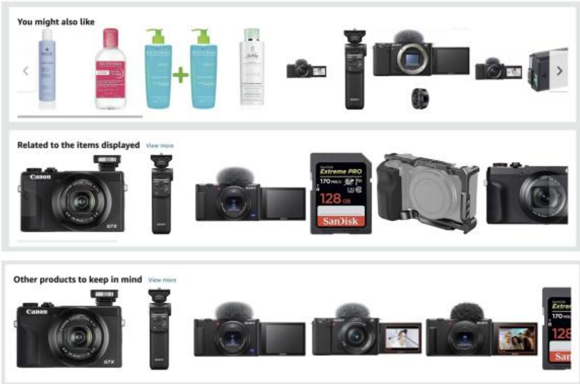

Figure 3.4 Recommendations of similar products in homepage

Amazon's homepage is composed of multiple blocks of different sizes. When the user scrolls down, they will see a product list generated based on the user's previous historical data, and even more similar products based on the newly recommended products(Figure 3.4).

Figure 3.5 Recommendations of similar products in product detail page

When click to enter a product details page, a recommended list of products of the same type will also appear(Figure 3.5). The products here are of the same type as the products on the current page.

- Based on users with similar interests

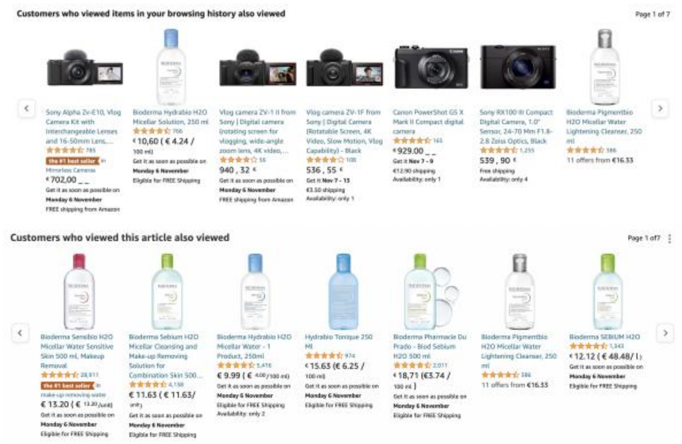

Figure 3.6 Recommendations based on similar users' interests

Based on the user's own browsing history or a specific product, Amazon will recommend other products that have been viewed by the users who have viewed the same products(Figure 3.6).

Efforts on user control and transparency

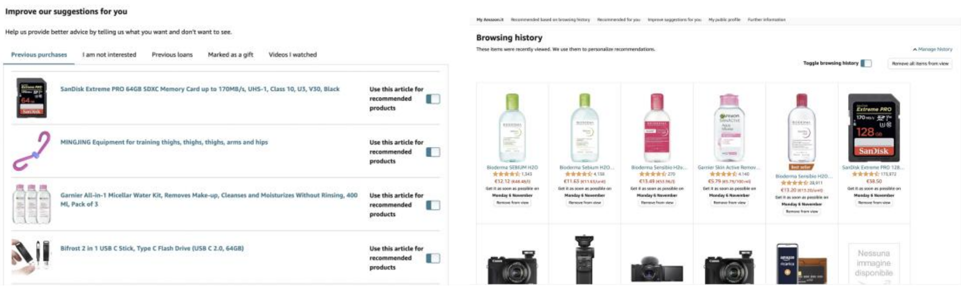

Figure 3.7 Switch to manage the preferences

In the user's browsing history page(Figure 3.7), users are able to delete some products. Such an operation can help the recommender system reduce the recommendation of some products that the user is no longer interested in. Similarly, in the list of previous purchased products, users can choose to cancel certain products to prevent the system from providing unnecessary recommendations.

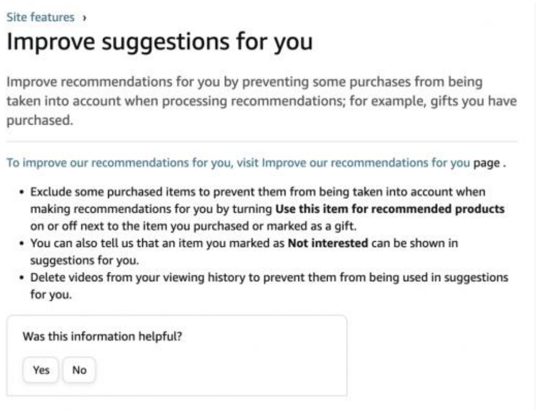

Figure 3.8 Explanation about the recommendations

Besides, Amazon has given users understandable explanations for the above-mentioned functions that can help the system adjust recommended content through their active operations(Figure 3.8). These instructions not only increase user engagement, but also help users understand the mechanism of the recommender system behind.

Considerations on serendipity

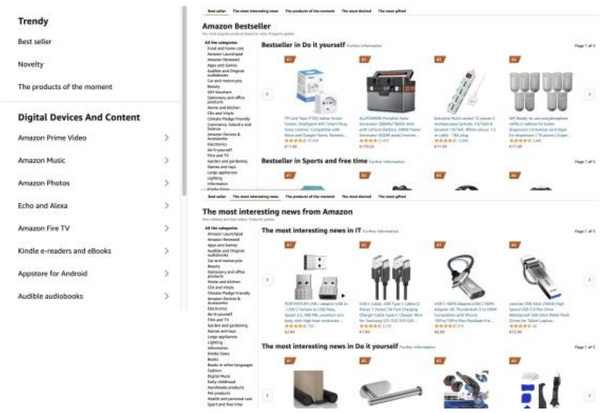

Figure 3.9 Recommendations for current trend

In order to prevent users from being limited to their own areas of interest and not being exposed to new content, Amazon will also recommend some products to users that they have never paid attention to. There is a dedicated part called "Trend" at the top of the side menu that is specially to providing a list of current hot-selling and novel products to help users open their horizons and keep up with the latest trends(Figure 3.9).

2. eBay

eBay is a highly influential multinational e-commerce website and has become one of the top ten e-commerce companies in the world. Today, eBay has 132 million active buyers in 190 markets around the world, and has

approximately 1.9 billion live listings. Users can buy almost anything they want on the platform. Here, both individuals and businesses can enter the platform to buy and sell products, so the number of products, richness of types, and frequency of updates are very high.

eBay uses artificial intelligence and machine learning technology to help drive the most advanced and scalable global marketplace. The core component of its recommendation engine is ranker, a machine learning technology that ranks items and then shows users the ones they may most prefer. There are many types of products on eBay and are short-lived, many items may not be listed again after existing on the platform for a week. Thus, the traditional collaborative filtering algorithm is not applicable here, because the available information on items purchased by the same user will not be enough to generate recommendations (Brovman 2016). Therefore, in general, the recommendation process of eBay's recommendation system can be divided into two steps. The first is Recall, which retrieves products similar to a given item to form candidate items. The second is ranking, in which candidate items are ranked according to the likelihood that the user will complete the purchase, and the top five products are finally offered to the user (Brovman 2016). In order to find high-quality similar items among a large number of products, eBay uses machine learning models to train based on the collected implicit user online behaviors, and uses deep and wide neural networks to simultaneously optimize click and purchase tags for ranking optimization (Zhou 2023).

Real-time recommended product list

- Based on user’s online activities

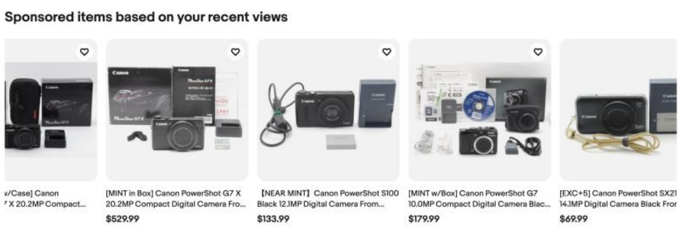

Figure 3.10 Recommendations based on browsing history

The module at the top of the homepage is used to display items recently viewed by users. The "Sponsored items inspired by your views" module under the platform homepage and product information can help evoke users' possible potential needs based on previous browsing records(Figure 3.10).

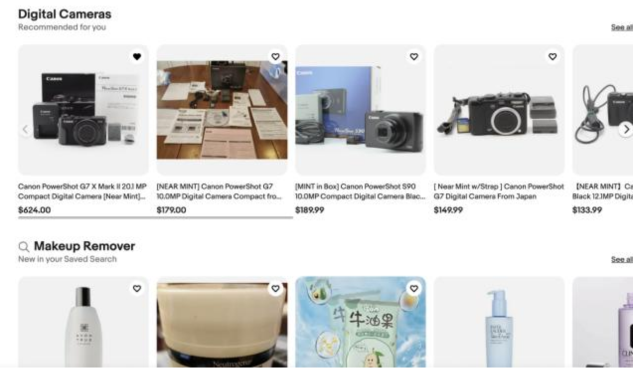

Figure 3.11 Recommendations for items of same type

The system will summarize the attributes of browsed products into a category and use it as a module to recommend items of the same type to users(Figure 3.11).

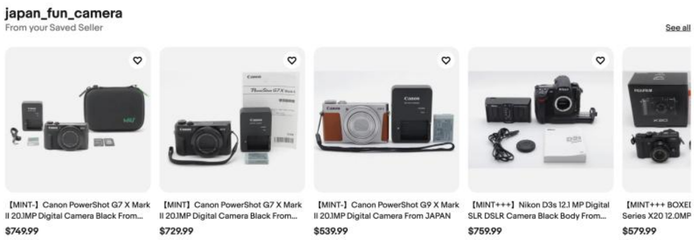

Figure 3.12 Recommendations for items sold by same sellers

For sellers that the user is interested in, the user can follow the seller, which makes it easier to catch up with the seller's new product updates. When a user starts following a seller, a module will appear on the platform homepage to recommend other items sold by the seller(Figure 3.12).

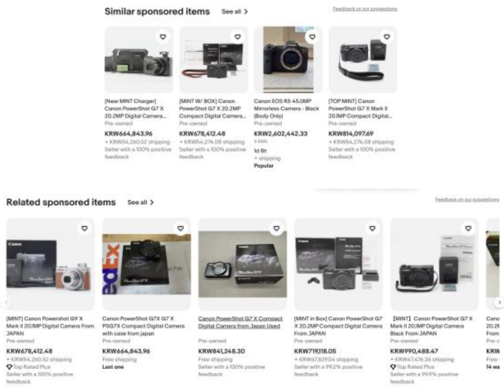

Figure 3.13 Recommendations for sponsored items

On the product page, there will be a recommended list "Similar sponsored items" below the product information to display the same product or similar products of the same type from different sellers. In order to promote the sales of related products, there will also be a "Related sponsored items" module to recommend items that belong to the same field(Figure 3.13). For example, if you check a certain camera, the system will recommend other models of cameras or camera batteries to you. This module generally appears at the stage when users have strong purchase intention, such as on the item details page and shopping cart.

Priority display of the products

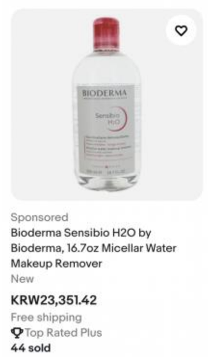

Figure 3.14 Sponsored item

Sponsored items(Figure 3.14) are products for which users, as sellers, pay a portion of the sale price to the platform in exchange for more exposure. Such items will also be prioritized in other users' recommendation lists.

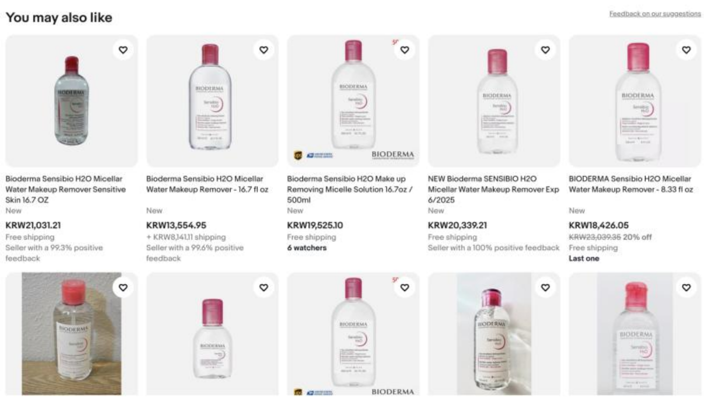

Figure 3.15 Prioritize display of new products

The system will give priority to displaying new products(Figure 3.15). In the product recommendation list, new products will usually be displayed in the first few positions. At the same time, the product information preview part of the list will be marked with a "New" sign.

Efforts on user control and transparency

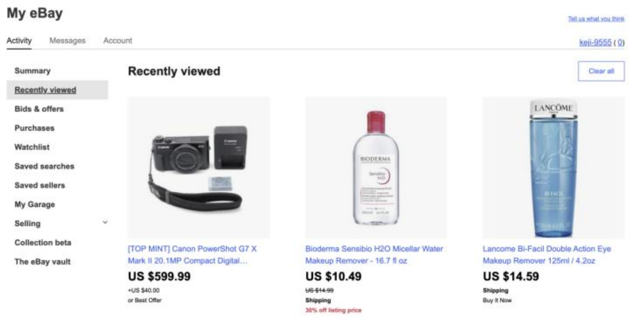

Figure 3.16 Users are able to clear all the history

Since a large part of eBay's recommendation system comes from users' online activities, on the My eBay page, users can prevent the system from continuing to recommend items they no longer need by clearing their browsing history(Figure 3.16).

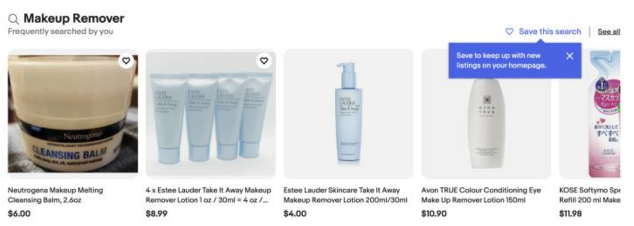

Figure 3.17 Save interested items

Users can also save the recommendation list generated based on the search history on the homepage by lighting up the heart as needed(Figure 3.17), so that they can easily view product categories that they are interested in for a long time. This is also a way to customize your own recommendations.

When users are interested in certain items that they do not have a strong intention to purchase, they can click on the heart in the upper right corner of the item in the recommended list to add it into the watchlist.

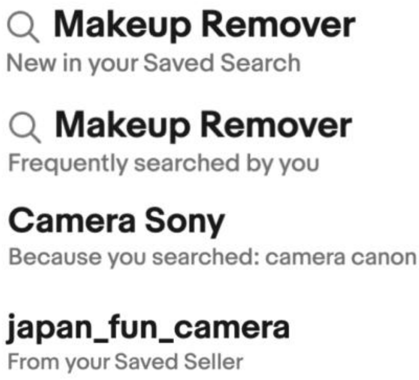

Figure 3.18 Explanations under each title

In order to let users understand the source of the recommended list, most of eBay's recommended lists will have explanation under the title(Figure 3.18), allowing users to understand why this series of products are recommended to users.

Feedback profile

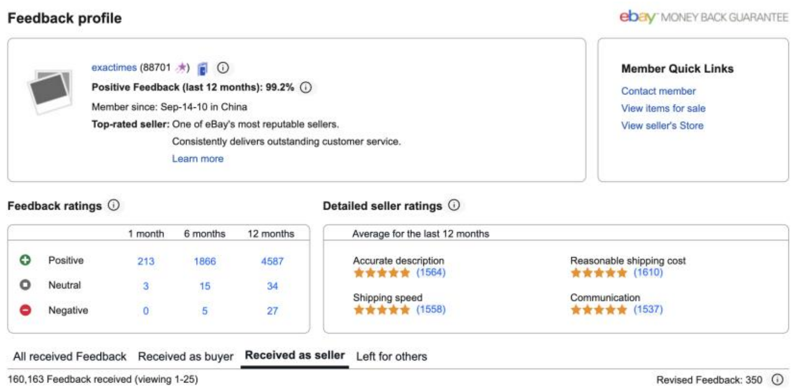

Figure 3.19 Feedback profile

Unlike most other e-commerce platforms, feedback in eBay is not about the product but about the user. Users here can not only be sellers, but also be buyers. After users buy something from a seller, they can evaluate and rate the seller(Figure 3.19). Meanwhile, the seller can also do the same to the buyer. On eBay, each user can play two roles at the same time, seller and buyer. Such an interesting setting simulates a more realistic trading environment, allows sellers and buyers to be in the same position for equal communication, which could promotes a better atmosphere.

3.2.2 Streaming Service Recommender System

1. YouTube

YouTube is world's leading video-sharing platform, which relies on its excellent recommender systems to suggest videos to users. As of 2022, YouTube has more than 75 billion visits globally. The number of users worldwide has exceeded 2.56 billion, and the average video viewing time per minute is as high as 694,000 minutes. As the video platform with the second highest number of active users in the world, YouTube has become the most popular video social media platform in the world. In order to improve the user experience, YouTube has done great effort from optimizing video length to increasing user satisfaction with videos since 2005, YouTube has been making unremitting efforts to promote the advancement of the recommendation system and and has created significant results so far. There are statistics show that 70% of the videos users watch on YouTube are driven by its system's recommendation engine.

YouTube's recommendation system is driven by artificial intelligence algorithms, which use machine learning to understand user behavior. It based on its recommendation algorithms to understand user preferences in order to provide users with the best, most engaging video.The working process of YouTube's recommender system can be summarized in two steps: the first step is to filter billions of videos into a few hundred candidates, and the second step is to continue to narrow down candidates and give them rankings. Usually, different users will get different results when searching for videos on YouTube, this is because the search algorithm has already been applied to the function. The algorithm takes into account two factors when providing recommendations to users: viewer preference and video quality. In more detail, keyword relevance, user engagement with the video (e.g., likes, comments, and shares), video quality (number of views and completion rate), and the user's search and watching history all influence the content of the recommendation list of video search results. This recommendation algorithm greatly enables users to find the highest quality videos that best match their preferences.

Presentation of Recommendations

- **Homepage**

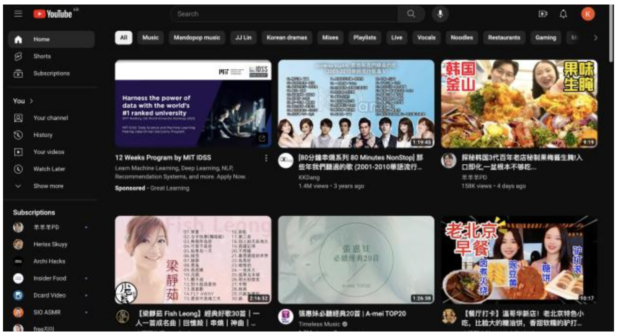

Figure 3.20 Recommendations on YouTube homepage

When visit YouTube website, the recommender system will help to provide viewers with a list of personalized videos based on their preference(Figure 3.20).

- **Searching result**

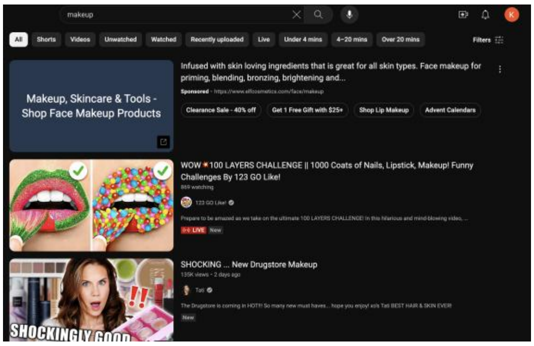

Figure 3.21 Recommendations in searching result

Recommended results are sorted based on how the searching keywords match the title, description, and video content and the quality of the video(Figure 3.21).

- Alongside the video the viewer is watching

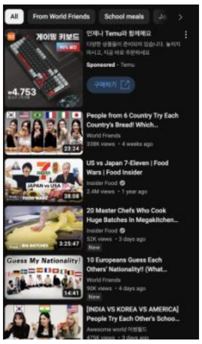

Figure 3.22 Recommendations alongside the video

According to the video relevance to the current video and user's searching history(Figure 3.22).

- After the video ends

Figure 3.23 Recommendations when the video ends

When current video finishes, the recommendation list is displayed in tiles with 12 videos(Figure 3.23). Recommended results are based on the topic of the current video and the video quality.

Efforts on user control and transparency

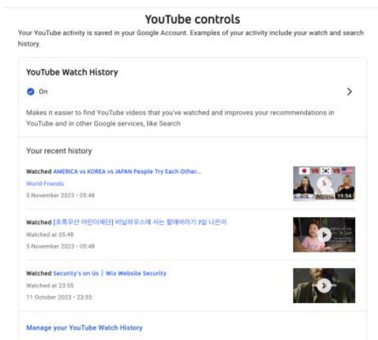

Figure 3.24 YouTube Controls

Users are able to view and manage their online activities on YouTube including watch and search history(Figure 3.24). Users can choose to turn on or off whether the system could record their activities or just exclude some subsettings. Thus, users will be given enough sense of control and better benefit personalize results.

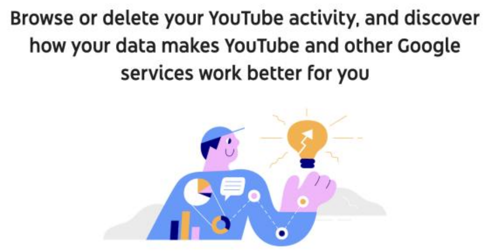

Figure 3.25 Explanation about the recommendation

In the data statistics page, users will be informed that their data will be used for personalized recommendations(Figure 3.25). Such transparency will give users a sense of trust.

Considerations on serendipity

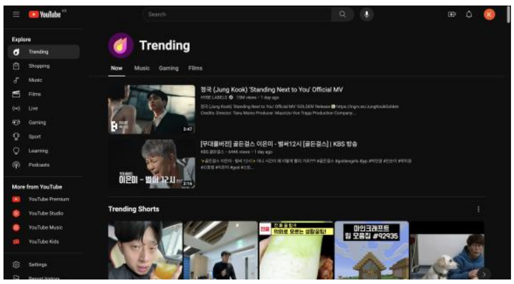

Figure 3.26 Recommendations for trending videos

The recommended videos in Trending are the hottest ones of the moment. YouTube’s recommender system derives rankings based on evaluating the number of views and quality of the videos(Figure 3.26). Trending is not personalized, but it can help users discover videos in areas they've rarely touched, and discover new interests

2. TikTok

With 3.5 billion installs, 1 billion active users per month, and more than 1.5 billion people using the app every day, TikTok has become one of the most popular social media platforms in the world. TikTok was formerly known as Musical.ly, an app focused on lip-syncing. Since it was acquired by ByteDance and renamed TikTok in 2018, its popularity has grown exponentially. The key to TikTok’s success and why it’s so addictive is the recommendation engine behind it, which can read your mind and keep you spending hours on TikTok without even realizing it.

The main goal of TikTok is to maximize user engagement and ownership retention. On the technical level, TikTok uses users' search history, viewing history, and online actions to predict user preferences, and uses powerful machine learning algorithms to provide users with personalized content. TikTok mainly uses two recommendation algorithms to collect and analyze user interests. The first is content-based filtering. Users' likes, collections, comments and shares will be used as data to influence the weight of the video and help recommend personalized content. Besides, context-related factors will also be taken into account, such as time of day, user location, etc. This algorithm ensures that recommended content is closely linked to user preferences. In order to give users the opportunity to discover potential new interests, TikTok also uses collaborative filtering recommendation algorithm to recommend new content to users. Through this, the system will use the user's profile and interaction with the video to evaluate the similarity between users, predicting which videos other users with similar interests like and recommending them to the user.

In addition, there are many times when users' preferences are transient and variable, and factors such as seasons, moods, can cause changes in users' preferences. This phenomenon is called concept drift. If just utilize basic machine learning algorithms to make predictions, it may result in inaccurate recommendation results. Therefore, TikTok team designed the Monolith system to mitigate this trend, making the recommended content for users more adaptable to their changing preferences and provide with more accurate results.

Efforts on user control and transparency

- **Keywords filtering**

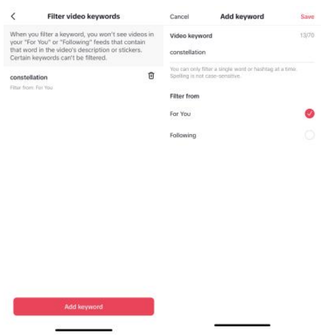

Figure 3.27 Keywords filtering in settings

Users can reduce the recommendation of some types of videos by adding certain keywords. They can click to add a keyword blacklist in Content Preferences of Settings and Privacy, and then save the settings(Figure 3.27).

Figure 3.28 Recommendations for videos with certain hashtags

For the interested hashtags, users can choose to filter videos of this type by clicking on the hashtag at the bottom of the video. For the uninterested ones, when tap on "not interested", the system will provide hashtags that related to the video and users can choose to filter some of them to reduce the similar types(Figure 3.28).

- Not interested

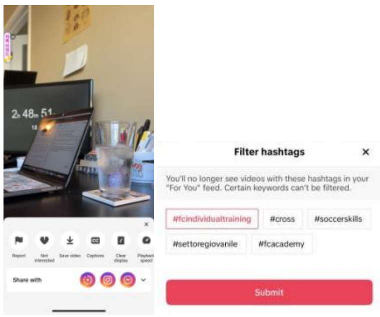

Figure 3.29 Filter hashtags

While watching a video, if the users see a video they don't like, it's easy to reduce the recommendation of certain videos. Users can tap the "Not Interested" button by long-pressing the video or clicking the Share button on the side to help the system reduce the recommendation of this type of video. They are also able to use hashtags filtering to avoid similar recommendations(Figure 3.29).

- Refresh your feed

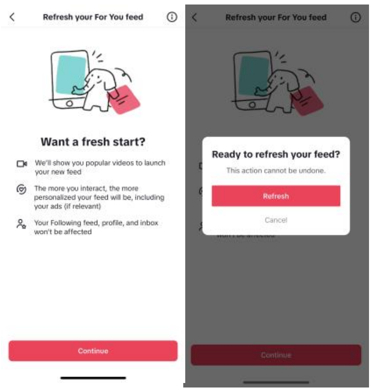

Figure 3.30 Refresh the feed

If the user feels that the current video stream is no longer interesting, they can refresh the feed in the settings as if they just signed up a new account(Figure 3.30).

- Why this video

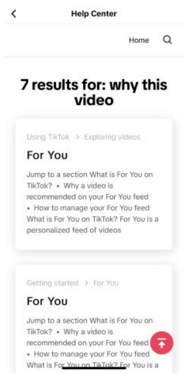

Figure 3.31 Explanations for the video recommendation principle

In order for users to understand why the video is recommended to them, TikTok also has a dedicated section to explain why the video is recommended(Figure 3.31).

Considerations on serendipity

In order to break the repetitive pattern, TikTok will not recommend repeated content to users, and videos that have already been watched will not appear again. Recommender systems also intersperse different types of content with content known to be of interest, avoiding the risk of homogeneous video streams.

3.3 Comparison

In this section, I will compare the two groups of platforms analyzed in the previous section and summarize the differences and reasons for the recommender systems of two different platform types in the same field.

eBay's recommended content is mainly displayed to users through different recommendation modules, while Amazon's recommender system, in addition to recommendation modules on the homepage and product details page, also has an independent recommendation module specifically used to display recommendations prepared for users. Both platforms will provide clear explanations to users, allowing users to understand the source of the recommendation lists they obtain, making users more trustful in the system. Besides, in order to increase the diversity of the system, they all provide users with a module in the main menu to display current trends and allow users to access the most popular products.

A special consideration for eBay's recommended content is its Sponsored mechanism. Users can have extra spend on their items to gain more exposure for their products, and such products will be prioritized in the recommended lists of other users.

For Amazon, the quality of the items offered on the platform is more important to the user. Amazon is more stringent in vetting merchants for their items, thus very few users sell on the platform as individual sellers, and its items usually come from larger suppliers. Amazon users can only spend money on the platform as a buyer, and the their goal is to find a satisfactory product. On the other hand, eBay is an auction platform, where sellers and buyers have the right to make two-way choices, and users can have the status of both sellers and buyers at the same time.

Compared with Amazon, the items are shorter-lived on eBay, the sales time often lasts no more than a week. This is because the suppliers of items on eBay are mostly from individuals and usually have small inventories, so it is meaningless for eBay to rate the items. Therefore, depending on the length of time the item has been sold on the platform, as well as the difference in the transaction methods of the two platforms, Amazon’s feedback system is for the product itself, while eBay’s is for the user. When we click on a user's homepage, you can see the evaluation of dual identity as a buyer and a seller. The short retention time of items on eBay also determines that its recommendation algorithm cannot rely on collaborative filtering, which is also a major difference between it and Amazon's algorithm. Therefore, eBay mainly generates rankings of similar items based on users' online interactions and the similarity of preferred items, and recommends top-ranked products to users.

Although YouTube and TikTok are both platforms in the video field, their recommender systems are very different due to the different length of videos they provide.

YouTube's recommendations are always presented in the form of a list, and its recommendation list is filtered based on user preferences and video quality. Whether it is on the user's homepage, appears in the user's search results, or is displayed at the end of the video, users can select the most attractive video to watch from the recommendation list via the video cover. TikTok, on the other hand, integrates recommendations into streaming media, and users cannot make direct choices. While ensuring that the recommended content meets the user's interests, each next video is uncertain and brings a sense of surprise to the user to a certain extent.

In terms of user control, due to the difference of the platforms, YouTube's functions are more comprehensive, while TikTok's user-controlled operations are more detailed and convenient. Like other website platforms, YouTube users can see their viewing history and decide whether to consider it as a factor in recommending content. In addition to commenting and sharing, TikTok users can also add filters through simple operations to further enhance personalized control. There are multiple entrances for each operation, such as adding a filtered hashtag, which can be reached by long pressing the video or pressing the share button. Compared with the strict control of video quality by long video platforms, short video platforms pay more attention to the immersive experience of users and will focus more on the users' immediate feelings when watching streaming media.

Both platforms will provide users with popular videos and increase the variety of video types. YouTube has a dedicated module to help users explore the latest trends, while TikTok provides users with a list of hot topics in text form. If users are interested, they can click to watch related videos from the search page. At the same time, popular videos may be recommended directly to users from the homepage, avoiding additional operations and increasing the user's immersive experience.

4. Understanding Information Overload

4.1 Information Overload

Nowadays, the amount of information continues to grow exponentially. With the development of technology, people's accessibility to information continues to increase, and "information overload" begins to occupy an important position in people's online experience. Information overload usually refers to the phenomenon that when people are confronted with too much information, the amount of information exceeds the limit of what the brain can process in a short period of time, making it difficult for them to make judgments and effective decisions.

According to (Belabbes 2023,144-159), there are five "triggers" that may lead to information overload, including an individual's cognitive state, a poorly defined information need, the characteristics of the information, the environment of the information or the environment in which an individual interacts with information. These triggers can also be summarized in terms of the user, the characteristics of the information and the external environment (Figure 4.1).

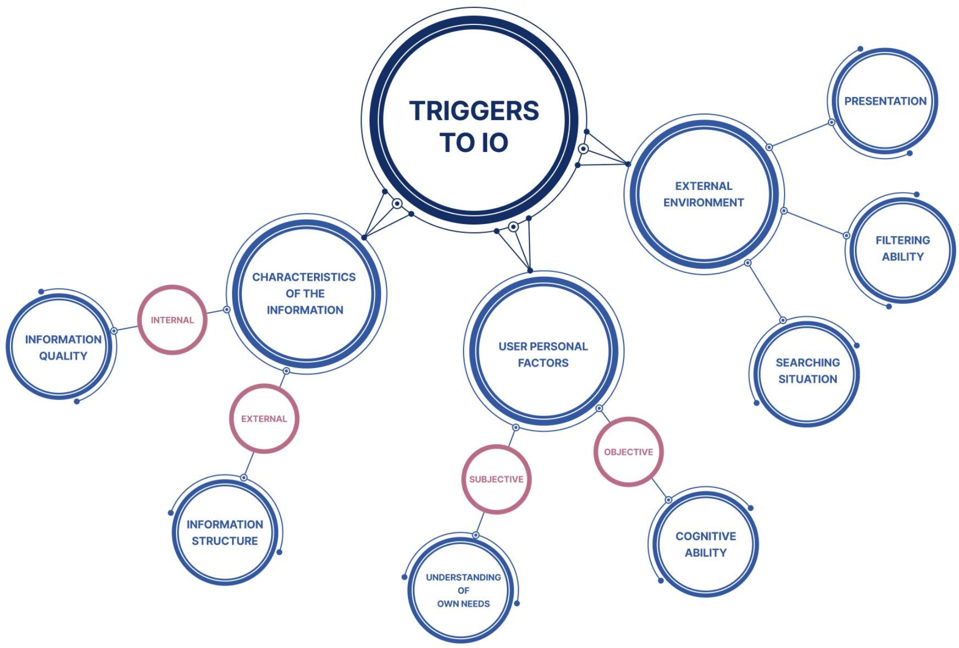

Figure 4.1 Triggers to information overload

First of all, the factors related to the user can be divided into objective and subjective factors. The cognitive ability of each person's brain is different, which is not only related to individual diversity such as gender, age and nationality (Matthes 2020), but also related to the cultivation of later life, that is to say, for various types of information, the individual specializes in different fields may cause differences in their cognition of information. In addition, the degree to which the information matches the user's needs also has an impact. If the user's lack of understanding of what he or she wants to find leads to an unclear definition of the information content, then the user may be exposed to a large amount of irrelevant information during the process of searching for and receiving information, and thus information overload may occur.

Secondly, both internal and external characteristics of the information may affect the role of information overload on the user. The internal characteristics of information mainly refer to the quality of information. The relevance of information to the user's needs and the diversity of information may affect information overload. In addition, information structure may also affect information overload (Lurie 2004), the change of information structure will affect the amount of information in each element, the user's acquisition to information will also change, and the amount of information obtained will affect the quality of decision making by the user.

Third, external environmental factors are relatively objective triggers. On the one hand, the situation where user search for information matters, such as the high difficulty of the task and the short time available to complete the task, may cause information overload. On the other hand, the filtering ability of the system according to user needs and the recommendation presentation have a significant impact on information overload. Both of them make up the recommender systems that are popularly used on various platforms today. The complexity of the navigation bar, the quantity and quality of the recommendations, and the presentation of the recommendations are all important to users when using recommender systems. A good recommender system filters the information using the best suitable recommendation algorithms and presents it to the user in the most satisfying design.

In conclusion, the phenomenon of "information overload" has become a prominent factor for users' online experiences. Information overload occurs when the volume of information surpasses the brain's capacity for rapid processing, which impede effective judgment and decision-making. It is influenced by a complex interplay of factors, users, information, and the external environment. User-related factors include cognitive diversity and the clarity of information needs, while information attributes involve quality, relevance, and structural factors. Additionally, the external environment, such as task difficulty and time limit, can exacerbate information overload as well. Nowadays, the omnipresence of recommender systems further

amplifies this challenge. Although the appearance of recommender system helps to alleviate information overload, the quality, quantity, and presentation of the recommendations will all impact the problem.

4.2 Effects on Users

Information overload can have a series of knock-on effects on people's emotions, efficiency and decision-making processes. Overall, when people are confronted with information that is too complex, too extensive or contradictory, they are likely to be unable to process and use it effectively. (Roetzel 2019). "This is likely to lead to fatigue and information anxiety as well as stress (Ndumu 2020, 869-891). In addition to possibly affecting people's work-study efficiency and creativity, at the psychological level, it may trigger a crisis of trust, a decline in happiness and even depression (Matthes 2020).

In the information age, the emergence of information systems has dramatically increased the speed of information processing. It helps people to generalize and manage data in large amounts, which can also facilitate the processing of larger amounts of information at the same time. Larger streams of data may trigger potential data overload problems. Individuals have different abilities to adapt to efficient systems because of differences in the thinking patterns of people. That is to say, each individual has a different speed in information retrieval and processing, which may lead to a decrease in the user's decision-making ability triggered by problems with the search strategy (Roetzel 2018, 1-44). It may result in induced stress due to the loss of control over information, leading to reduced productivity and, in the case of companies, even the phenomenon of quitting or termination of cooperation (Swar 2017, 416-425), which ultimately results in financial losses.

In addition, with the explosive rise of social media in recent years, people will unknowingly spend a lot of time every day indulging in watching endless short videos. The high-frequency use of social media also implies the continuous reception of massive amounts of information, which is also a kind of information overload. This can affect people's daily routines and the time they can spend on other activities, and people can significantly reduce the time they have to think (Misuraca 2013, 176-180). In addition, close contact with social networks and too much socializing in the virtual world can easily lead to feelings of exhaustion. Frequent communication, such as likes and comments, also distracts people's attention and creates an additional cognitive load. Because people's attention is generally continuous, interruptions require additional time to regain the previous state of concentration. External interruptions can conflict with planned tasks, which can trigger the development of anxiety. After people realize this negative

consequence, there is a great possibility of stress and regret, and this negative emotion can in turn have an adverse effect on people's daily life.

In the information age, there is a high probability that people will deeply experience the problem of information overload. In the ubiquitous flood of data, people are forced to seek strategies to take control, manage emotions, and ultimately make the best decisions within their initial capabilities. We need to focus on how to help users capitalize on the benefits of the age of digital abundance while mitigating its overwhelming effects.

4.3 How Recommender Systems Contribute

In the digital age of information explosion, recommender systems provide people with assistance in guiding them to their goals in the huge flood of information. The earliest function of recommender system was not so complicated as it is now. Initially, it was used as a kind of collaborative filtering technology to screen emails, which could complete filtering and browsing emails and some other functional operations. Today, recommender systems have been in development for more than thirty years. In an era of increasing demand for recommender systems, they have gone through many iterations and improvements. The initial focus was on the connection between user interests and item attributes, and then it began to focus on recommendations based on user profiling, and later began to consider the impact of user emotions and psychological factors on decision-making. Nowadays, the popularity of recommender systems in various fields can help users to cope with the complex data environment.

Here, based on the analysis of the possible causes of information overload discussed in the previous sections, I will analyze the contribution of recommender systems to the mitigation of the information overload problem.

1. Personalized Content

When faced with the same information, people may have different approaches to deal with the problem due to their different cognitive states. For example, older people are more likely to click on unread information than younger people. In order to provide more satisfactory recommendation results, it is needed to customize the recommendation content or recommendation method for different types of people.

There are many factors that affect people's cognitive state, among which personality traits are a very important part (Paryudi 2022, 360-361). There are two ways to obtain personality traits, explicit and implicit ways. The former usually requires users to complete a questionnaire or personality test in advance, which is troublesome and time-consuming. It is not suitable for users who want to save costs before using recommender systems. Therefore, there is a technology called Personality Elicitation from Text (PET), which can understand the personality traits of users through their social media accounts implicitly. In addition, previous studies have shown that demographic data can be used to predict personality traits. Based on this, there is a recommender system called demographic recommender system (DRS), which can predict users' preferences from their demographic data (Al-Shamri 2016, 175). The demographic data, including age, gender, occupation, and even hobbies and blood type, can be used to predict personality traits. When other preferences are the same, personality traits could be used to help provide users with more accurate recommendations and prevent unnecessary displeasure.

2. Information Refinement

When users are searching for desired items or videos, the more thoroughly they understand their goals and the more purposeful they are in their search, the closer the keywords they can input to the system will be to their ultimate needs. In this way, the recommender system is more likely to help the user to provide them with recommended results that meet their needs. That is to say, when the user's goal is clearly defined, the less difficult it is to provide recommendations. However, when users do not have a clear definition of their needs, this ambiguity can lead to information overload as they are faced with a large amount of irrelevant information. Recommender systems can help users understand their own perceptions and gradually approach their real needs.

Traditional recommender systems usually use collaborative filtering, content-based filtering, or hybrid models to explore user’s preference. In recent years, deep learning is becoming a more widely used technique due to its ability to process user data in a detailed way, which results in highly personalized recommendations. Compared with traditional algorithms, deep learning models are able to understand and process more complex user behavior. It analyzes user interaction history and preferences through multi-layer neural networks, which can identify complex patterns and relationships, leading to more accurate recommendations (Zhang 2019). People's research on recommendation algorithms is in progress, and continuously optimized recommender systems understand users better. Recommender systems is helping users reduce their cognitive load and ensuring that they get the results that best meet their cognitive needs.

3. Content Optimization

In order to ensure that the recommendations provided to the user are of the highest quality and relevance, in addition to appropriate filtering algorithms, creating a feedback loop is necessary as well.

Feedback information techniques are categorized into explicit and implicit feedback (Núñez-Valdéz 2018, 89). Explicit feedback allows users to indicate their interest, which enables users to rate, comment, or otherwise provide feedback to the system. Implicit feedback is usually obtained without user's awareness.

The system captures, analyzes, and processes the user's behavior when they are using the system, such as clicks, scrolling, sharing, and dwell time. This data is then converted into explicit data for analysis. For example, Click-Through Rate (CTR) can be used to measure the frequency of a user clicks on a recommendation, and Conversion Rate is how often a user completes a purchase after clicking on a recommended product (Kelly 2001). A high Conversion Rate means that the system not only optimizes the content, but also enhances the user's decision-making process. This feedback loop allows the system to continually evaluate the performance of the system, optimizing recommendations and enhancing the user experience.

4. Adaptive User Environment

The environment of people's daily life is constantly changing. Although recommender systems always make efforts to find users' personalized recommendations, the influence of external factors on users' preferences cannot be ignored. Context-aware recommender systems (CARS) focus on various contextual factors, such as location, time of day, user device, weather, and user behavior, and match the external factors with current needs (Ali 2023). In order to provide real-time personalized recommendations, it can effectively identify changes in the environment and take into account the dynamic interplay of contextual factors (Raza 2019, 92-93. Panniello 2012, 43). For example, a restaurant app's recommendation system can adjust its suggestions based on the user's current location and the time of day — if a user is in London, the system might recommend nearby landmarks, restaurants, or cultural events; conversely, when he/she gets back home, the recommendations will be more focused on local activities.

In addition to providing more and more personalized recommendations, context-aware recommender system can also increase user engagement, because when they receive recommendations that fit the current context, users are more likely to take action.

As technology and data collection methods evolving, context-aware recommendations are expected to become an integral part of applications, ranging from e-commerce and entertainment to health and travel.

5. Diverse Exposure

Recommender systems aim to provide users with recommendations that are more in line with their preferences, and experiments in 2017 have shown that most recommender systems reduce diversity by focusing on accuracy

(Kunaver 2017). Therefore, it is easy for users to be constantly exposed to content that matches their pre-existing preferences, leading to homogenization of information. In contrast, in a 2013 user study, it was shown that while increasing the diversity of recommendation lists does reduce user acceptance, it increases user satisfaction instead. Because content provided by diversity may not directly align with users' preferences, these recommendations introduce users to information, products, and ideas that they may not otherwise encounter. Yet, it may arouse their interest and promote exploration outside their comfort zone which leads to an increasing user engagement.

Today's researchers have recognized the importance of diversity, and that increasing diversity does not necessarily mean decreasing accuracy. If used in the right way, with new algorithms design, it can actually allow for both, leading to a richer recommender systems

5. The Dark Side: How Recommender Systems Can Overload Us

The main purpose of recommender systems is to help people filter useful information in the information flooding, thus reducing possible information overload. In today's era, where recommender systems are being used by almost all the platforms in varied fields to optimize content recommendations, everyone is constantly optimizing their recommendation algorithms and presentation of recommender systems, so as to maximize the user experience. However, the development of an excellent recommendation system needs to take into account many factors, from the quality of the recommended content to the presentation methods will have much impact on the user experience. If there are problems in managing recommendations, it may not only fail to reduce the phenomenon of information overload, but also lead to some new problems.

Therefore, in this chapter, by thinking about the causes of information overload and analyzing the use cases of the excellent cases in Chapter 3, I elaborate the possible negative impacts of recommender systems in four points, so as to help check the important points when building and improving recommender systems. After that, I analyzed the model Recommender systems' Quality of user experience (ResQue) proposed by Pearl.P and Li.C, which intends to evaluate the recommenders' perceived attributes. By understanding users' perceptions and corresponding behaviors, I explained the reasons why recommendation systems can cause psychological overwhelm in users, and proposed some possible strategies that could alleviate the problems.

5.1 Identify Negative Effects

- Perceived Information Overload

Information overload occurs when people need to make decisions when the amount of information they face is greater than their ability to process the information (Schroder 1967). Perceived overload is more subjective than information overload. It refers to the cognitive pressure that occurs when people face a large amount of information and feel that they have a lot to do. According to research (Aljukhadar 2010), information overload has a certain effect on perceived overload. Although the relationship between the two does not increase linearly, the overall trend is upward. In other words, as information overload increases, perceived overload will also increase.

In the study of (Chung 2023), perceived information overload is summarized as the phenomenon that users receive too much information from push notifications and recommended videos of short video applications in a period of time. Research has found that information overload in short videos may increase users' intention to stop using short video applications. This is consistent with the information overload phenomenon in the streaming media field discussed in this article. That is to say, if users are attracted by a steady stream of videos that meet their preferences, it will indeed increase user engagement in a short period of time, but when users stay on the platform for too long, it is likely to lead to social media fatigue. Similarly, in the field of e-commerce, since recommendation results are based on real-time changes in user interaction, users may see the recommendation module after clicking on a link, and then keep clicking into new item pages. This happens more often when users are not particularly clear about their needs. They will keep seeing the items they are interested in and get stuck in endless lower-level web pages. In the end, they may even forget what their original goal was. Too rich recommendation results may lead to this phenomenon, and users will feel dazzled. Information overload usually occurs when users are faced with a large amount of information that does or does not meet their needs, and perceived overload at this time may occur when they are facing a large amount of information that suits their interests.

This negative effect is an additional product of the current development of recommender systems and the pursuit of personalized recommendation results. These are possible negative phenomena resulting from content optimization due to good recommendation engines, but instead of changing the recommendation algorithms for this reason, we should look for other strategies to help users reduce fatigue due to perceived overload.

- **Filter Bubble and Echo Chamber**

Recommendation systems usually help users filter out a large amount of irrelevant information and provide users with personalized recommendations. From optimizing recommendation algorithms to obtaining data that reflects user preferences from multiple channels, platforms have spent a lot of effort studying how to obtain users' most authentic preferences and improve their accuracy. However, the pursuit of extreme personalization of recommendation results often leads to a negative impact: filter bubbles and echo chambers.

The term "filter bubble" was coined by internet activist Eli Pariser around 2010 (The Filter Bubble, 2011). It refers to the user's interactions in the system, such as browsing records and search history. These data are collected over time and used for the analysis of the recommender system. Through algorithmic filtering, users can only be exposed to narrow information, which will lead to a limited vision. The concept of "echo chamber" is similar to that

of "filter bubble". Just like its name, recommender system are acting like an amplifier, communicating and repeating people's information in a closed system. Thereby, it will strengthen people's opinions, leading to the radicalization of people's views. The two concepts discussed here were originally discussed in the field of social media. Recommender systems only expose people to the information they want them to know, making them easier to manipulate. Instead of pursuing factual evidence, people will mistakenly believe that they are surrounded by people who agree with their opinions, causing the acceptance of the information that only conforms to their own views.

When extend to the field of streaming media, it is also of great research significance. In order to increase user participation and increase the users stay on the platform, the recommender system will provide users with information they are interested in to make them pleased. These results may appear in the default recommendation list on the homepage, the search results or in personalized ads. Users can be blocked from information related to their interests and unable to access new content. This also hinders users from discovering potential interests and exploring the possibility of more choices, and falls into a self-reinforcing cycle. In addition, many recommender systems will add social functions. When the user is browsing the content, there will be labels showing that their relatives and friends are also viewing it or the content has been recommended by them. Users will gain a sense of recognition from such labels, which can exacerbate the filter bubble. In terms of platform economic benefits, apart from content related to users' preferences, the recommender system will also give priority to providing content that is more in line with current trends or more popular to ensure higher popularity of the platform, which can cause higher profits. Such popular promotion is not conducive to users discovering non-mainstream content and may also strengthen filter bubbles.

- **Quality vs. Quantity**

The quality of the recommendation results provided by the recommender system will greatly affect users' satisfaction, and a large amount of low-quality recommendation content will also have a negative effect on users. Here, I analyzed factors that may affect the quality of recommendation results include the following two situations:

First, the recommendation results cannot adapt to the changing needs of users. When they use the platform and interact with the platform, the recommender system will continuously collect and store this type of data for analysis. However, changes in user behavior will bring about shifts in their interests that are difficult to predict. This result is usually different from the prediction results of the model, because it is based on the user's previous data collected from the platform and the recommender engine cannot fully

consider all factors that may affect user preferences. In short, the recommender system model may face the situation of using past data, but that information no longer meets the user's current needs, which results in inaccurate results. In order to deal with this situation, the TikTok team developed a machine learning algorithm called Monolith to quickly respond to changes in user preferences (Liu et al. 2022).

Second, the recommender system cannot effectively evaluate content quality, resulting in the inability to understand user satisfaction with the recommendation results timely, and therefore cannot formulate appropriate optimization strategies. Nowadays, many platforms have realized the filter bubble phenomenon that recommender systems may bring. In order to alleviate this impact, they have begun to pay more attention to increasing the diversity and serendipity of content in the recommendation results. In this way, users can not only see personalized recommendation results in the recommendation list, but also see many items from new fields. However, failure to control the proportion of diversity in the results may dilute the overall quality of the content, resulting in a mixture of high-quality and low-quality content. Without a sound quality control strategy for recommendation results, it will be difficult for users to distinguish between high-quality and low-quality content among the rich information.

- Lack of User Control

The working process of the recommender system is completed in the backstage of the system. From collecting data, filtering data to analyzing data, the recommender system uses complex recommendation algorithms for data processing. Only the stage of recommendation presentation will come to the user's vision. Therefore, it is often difficult for users to understand why they receive these recommendation results, nor do they know which of their data is used by the recommendation engine. These specific reasons are often kept in a black box (Amershi et al. 2019). Such non-disclosure of the underlying principles makes low-transparency recommender systems, which will have a negative effect on user satisfaction (Tintarev and Masthoff 2015) , making it difficult for users to make decisions based on the recommender results generated by the system.

Recommender systems need to analyze explicit and implicit user data to generate recommendation results. Generally speaking, recommendation results are automatically generated through algorithms. Users only need to use the platform's functions normally and do not need to actively participate in the work of the recommender system. However, there is research showing that user controllability can support exploratory search. User controllability refers to allowing users to gradually reduce the number of items in the process of finding results (Sciascio 2018). Improving user controllability can support exploratory search and encourage users to participate in the recommendation process through various inputs (Bostandjiev 2012). Therefore, if users do not have space to actively adjust the quality of results, the recommender system cannot provide users with sufficient options to further specify their preferences. Due to the diversity of factors that affect user preferences, most of which contain both objective and subjective elements, producing results based solely on the system's data analysis may lead to inaccurate recommendation results.

5.2 Why Recommender Systems Can Be Overwhelming

In the above section, I elaborated on the possible negative effects of recommender systems from four points. In this section, based on the Evaluation Framework on the Perceived Qualities of Recommenders (ResQue), I will analyze the influence and reasons that these negative effects may have on users from the perspective of user attitudes (Figure 5.1).

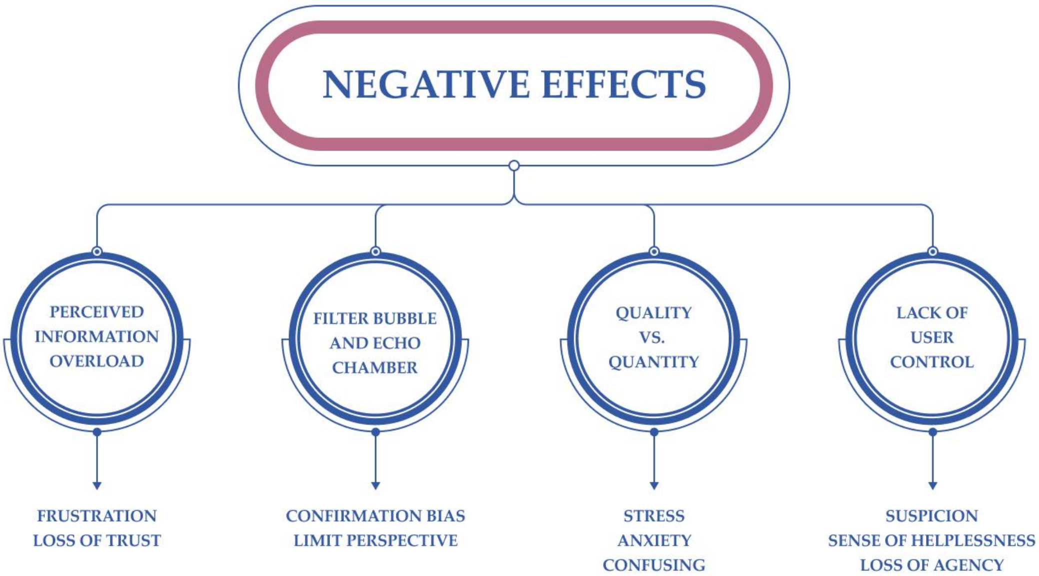

Figure 5.1 Negative effects and related user attitudes

Research has shown that users' perceived quality of a recommender system affects users' beliefs about its ease of use, usefulness, and control/transparency. Usually, users use recommender systems in the hope of getting useful information to support their decision-making. If the quality of recommendations can meet user needs, users will have a positive attitude, which is manifested in overall satisfaction, confidence in decision-making and trust in the recommender system. On the contrary, if there are various deficiencies in the quality of recommendations, there will be problems with the quality of the recommendation results and the user experience, which

will lead to negative emotions. Failure to obtain the desired results can cause users to feel that their time and energy have been wasted, which can cause a loss of trust to the system. Regarding the possible negative effects of the recommender system analyzed in the previous section, I will divide it into four corresponding points to discuss its emotional harm to users.

First, users typically have certain expectations when interacting with recommender systems and hope to discover valuable or enjoyable content. If this requirement cannot be met, users may become frustrated with the system and lose their trust. Since the content provided by the recommender system will always match the user's preferences, users will stay on the platform for a long time to browse a large number of recommendations. When there are too many recommended contents of the same level of interest while the system fails to help users make effective comparisons, it will prevent users from making good decisions, leading to fatigue caused by perceived overload. The impact of receiving a large amount of recommended content also occurs in the field of streaming media. Users will always spend much time on the application without realizing it. Excessive time consumption may delay people's original plan, which in turn leads to their regrets because the plan cannot be completed on time.

Second, in order to keep users engaged, recommender systems often present users with content they want to see, which can create filter bubbles and echo chambers. Such systems may inadvertently limit users' exposure to diverse perspectives and content, thereby promoting confirmation bias and preventing users from exploring new perspectives. As a result, users will be more likely to prefer information that confirms or reinforces their beliefs or values (Nickerson 1998). Moreover, when users are immersed in a large amount of information that agrees with their own opinions, they sometimes do not even realize that they have biases. In the end, once users discover the fact that they are isolated from external information, they may have painful emotions.

Third, too much low-quality recommended content will cause users to reduce their trust in the system. When faced with a large number of such recommended content, there will be consequences similar to information overload. Users can feel overwhelmed because they have trouble discerning what quality and useful information is, causing stress and anxiety. In addition, in order to improve user engagement, many recommender systems will introduce much novel content to surprise users. However, this can upset users by introducing unfamiliar or irrelevant items. It is not only troublesome for users to keep up with the constant influx of new recommendations, but difficult to find content relevant to their preferences, resulting in a confusing user experience.

Finally, the user's perception of the system lies in its ability to give the user control and to illustrate the recommendation rationale to demonstrate its

transparency. A lack of user control can result in users losing control of their data, which can lead to feeling a loss of agency and sense of helplessness. And if users are not able to fine-tune recommendations, they may receive results that do not match their current needs or desires, which may create a confusing feeling of disconnect. In addition, when users see recommended content that matches their preferences, they are usually curious about the reasons. They guess that their online behavior has been tracked by the system, but have no idea what data is collected and used by the system. The unknown about the working behind the recommender system may cause users to worry about privacy and security issues, thus creating anxiety and suspicion. Similarly, even if many recommender systems provide users with customized preference options, users do not know the role of their choices or fine-tuning and cannot see the reasons and results. Therefore, it is hard to encourage users to actively participate in recommendation optimization, and the lack of explanation will also increase user confusion and suspicion.

5.3 Possible Solutions and Strategies

In this chapter, I have analyzed and explained in detail the possible negative effects can cause by the recommender systems and their reasons. Based on this and combined with the analysis of cases in Chapter 3, the solutions to different potential problems have become clearer. Therefore, in this section, I will briefly summarize the possible solution and strategies to help understand more clearly what needs to be paid attention to in building a satisfying recommender system.

- **Explainable Recommendations**

It is crucial to improve the transparency of the system and let users understand the principles of the recommendation algorithm and how the system works. According to (Jannach 2019, 4), sufficient explanations can be provided to improve users' trust, which can also be used as a starting point to help give user control.

The explanations of recommender systems can be divided into two aspects. One is to tell users why they see this recommendation. A good example is that the source of the recommendations will be stated in the title of each recommendation module on eBay, such as "Frequently searched by you". There are also recommendations related to the collaborative filtering algorithm, and the results will be based on other users' data. Here, Amazon uses "Customers who viewed this article also viewed" as a title of the recommendation module to show users the reason. The second is to provide users with a guarantee of privacy security. The system needs to ensure that the data collected from users is properly stored or completely cleared

regularly, and it also needs to indicate that the data will not be used for other purposes. The text content of these explanations needs to be more specific and simple to understand, so that it does not become meaningless because of being too general, nor does it cause additional burden to the user because of being too complicated. No matter which explanation is given, the purpose is to tell users that the effort we do is to provide you with better services and provide users with sufficient security, thereby gaining user loyalty.

- User-Centric Controls

Usually user control in recommender systems includes transparency, explanation, user feedback, etc. Here I will narrow its scope and focus on the user control of recommended content through specific user operations. The system needs to allow users to adjust or correct information related to their preferences, allowing them to choose which data is worth using and which data is no longer valuable. Users can prioritize data from different sources, and in the same way, the weights of different data can be adjusted to increase the usage of data that users believe better reflects their true preferences. For some data, other contextual factors need to be considered to determine whether the data is useful, this requires user participation to help personalized recommendations. For example, a user searches for dog toys just because his friend has a dog and he wants to give him a gift, but the user himself does not actually have a pet. If the system continues to recommend related products every time the user makes an online purchase, the quality of the overall results may be reduced. For this type of data, the system needs to allow users to delete certain records and choose which types of data are no longer needed for recommendations. In short, recommender systems should give users detailed options, so they can freely make personal adjustments feel a great sense of control.

- Diversity and Serendipity

To prevent filter bubbles, recommender systems need to introduce novelty in recommendations and allow users to explore outside their comfort zones. Therefore, functional modules can be created in the system to allow users to discover new topics or explore diversification. For example, the platform can add rankings based on current trends to the platform, and popular content will have a greater probability of attracting users. Taking user control into consideration, the system can also add two different modes, one focusing on personalized recommendations, and the other providing more diverse content, and users can switch at any time according to needs. In addition, the system can allow users to plan according to their own preferences and create personalized lists in different categories to collect content of interest. The diversification of recommended content gives users the opportunity to be

exposed to new content, which encourages users to explore new areas and discover their new interests. However, the system needs to pay attention to balancing personalization and novelty to prevent too much new content from taking over the main content.

- **User Feedback Loop**

Good recommender systems conduct regular evaluations to identify and correct possible biases in recommendation results. The evaluation of the system comes not only from regular testing within the system, but also from making full use of user suggestions.

Clear user feedback methods must be established to enable users to report concerns, biases, or issues, and they are able to provide feedback on how the information is interpreted and relevant. The platform needs to provide multiple entrances that are easy for users to detect, especially on pages for displaying recommended results, so that users can provide feedback at any time with low effort. For example, there will always be an icon with "feedback" on it fixed on eBay's item details page. Its position will not change as the page scrolls, and users can easily find it and submit feedback. In addition, the form of feedback should be as concise and clear as possible. It can allow users to evaluate their satisfaction of the current recommendations by clicking different number of stars, or use a method similar to A/B testing to let users select a more satisfactory option among options. Since providing feedback is not the main purpose of using the platform, the system needs to choose a way to obtain feedback from users that costs minimum effort. Besides, timely response to user feedback is important as well, because users need to feel that their voices are heard and that they have participated in the recommended results they obtain. This can not only mobilize the enthusiasm of users, but also make users more motivated to continue to help optimize recommendation quality, forming a positive cycle.

6. Balancing Personalization and Avoiding Overload

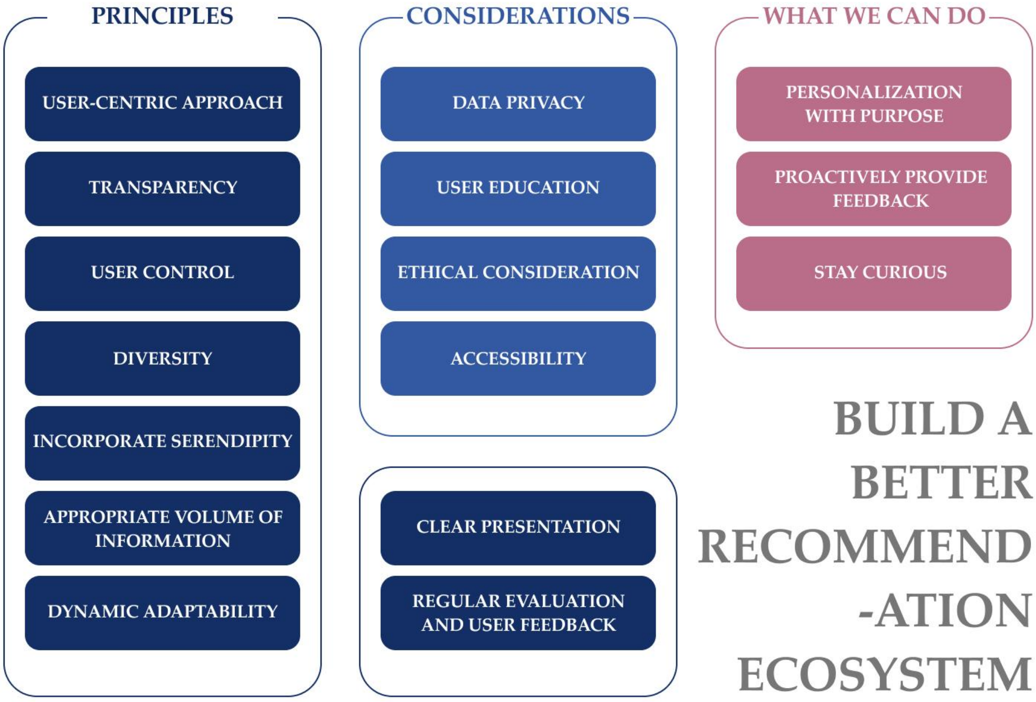

Figure 6.1 Principles, considerations and what users can do to build a better recommender ecosystem

6.1 Finding the Right Balance

In the previous chapter, we discuss the negative effects that recommender systems may have on the way to pursuing personalization, and proposed strategic directions to address these issues. In order to reduce the information overload that users may encounter and improve the accuracy of personalized recommendation results, recommender systems may instead overload users. Therefore, we believe that striking a balance between personalization and preventing overload is a major challenge recommender systems are facing today. This section will explore the principles and considerations involved in achieving this balance, helping the recommender system to enhance the user's personalized experience while also preventing the potential dangers, so that users do not feel overwhelmed when receiving valuable content (Figure 6.1).

• **Principles**

Principles are the guidelines of the overall approach and mindset applied when designing recommender systems. It helps to clarify the goals and philosophy behind achieving the balance of personalization and avoiding overload.

1. User-centric Approach

When the recommender system provides recommendations to users, it needs to give priority to user preferences and explore personalized recommendations that best meet the user's current needs. Even in order to enrich the diversity of results, we must be as user-centered as possible to ensure that the system's personalization work can promote user experience and prevent overwhelming experience.

2. Transparency

The recommender system needs to let users understand how it works and what data the system collects. It should let users understand which of their own data is used as the basis for generating recommended results, and how this data is used. This can help users understand the principles of recommendation algorithms and the influencing factors, which can help to improve their trust in the system.

3. User Control

Recommender systems need to allow users to have control over their own data, which means users are able to adjust recommendation settings and specify which data is valuable or which data does not need to be considered anymore. This can not only help the system effectively optimize recommendation results, but also improve user participation and give users a sense of control over recommendations.

4. Diversity

The system needs to make effort on providing users with diverse recommendations and improving the comprehensiveness of the results. This prevents users from being limited to their own preferences and prevents the filter bubble. Displaying rich content to users and encouraging users to discover potential interests can not only mobilize users' interests and prevent information overload, but also contribute to the commercial development of the system.

5. Incorporate Serendipity

In addition to providing users with a variety of recommendations to ensure the diversity of results, recommender systems also need to improve the novelty of recommendations to promote a more engaging and enjoyable experience. In addition to being consistent with user preferences, the recommended content can also provide users with some relevant but unexpected content to give users a sense of surprise.

6. Appropriate Volume of Information

Recommender systems aim to help users reduce information overload, so when providing users with filtered personalized items, they must always remember to provide users with an appropriate amount of information. When displaying recommended results, the system needs to control the number and frequency. Also, they could arouse users awareness of too much information received before they feel fatigue them selves. The system can add reminders to prompt users to take a proper rest or show users the number of recommended results they have browsed to prevent information overload.

7. Dynamic Adaptability

Recommender systems need to continuously adapt to users' various behaviors and make real-time adjustments to these changes. It is useful for the systems to choose algorithms that can learn in real time through user behavior and continuously collect user feedback, which can help to provide users with recommendation results that are always consistent with their preferences.

8. Clear Presentation

The form in which the recommender system displays content to users should be clear and organized to ensure a user-friendly interface. Even with valuable recommendations, users can still feel overwhelmed if the presentation is cluttered and chaotic. The system can promote user understanding and decision-making by using appropriate designs, such as dividing recommendation modules, clarifying the sources of recommendations, selecting an appropriate number of recommendations, and using icons to highlight important information.

9. Regular Evaluation and User Feedback

The recommender system needs to regularly evaluate all aspects of the system indicators, which not only needs to come from the self-evaluation of the internal algorithms, but also considers the user's satisfaction with the system. The system needs to provide users with multiple convenient feedback channels, regularly collect user ratings, opinions and suggestions, then make adjustments based on the feedbacks. This will support the system's ongoing development and encourage its continual improvement.

- Considerations

Considerations help to remind of the elements that need to be taken into account when building a recommender system, and that it is important to be aware of these considerations in order to effectively realize the principles.

1. Data Privacy

Recommender systems must ensure that the user data complies with privacy norms and regulations, the data must be collected within a reasonable scope and properly stored. In addition, the system also needs to declare to users the privacy and security of the recommender system, provide users with sufficient sense of security, and ensure users' trust in the system.

2. User Education

Whether it is the use of the system or the understanding of related functions of the recommender system, the system needs to provide users with sufficient guidance. In order for users to take advantage of the recommender system, we should introduce them to relevant functions, walk them through the fundamental operating procedures, and assist them in exploring every function that is offered.

3. Ethical Consideration

In the development process of the recommender system, we need to pay attention to the fairness of the content provided to various groups. We should try to avoid potential bias and discriminatory practices, and create an inclusive recommendation environment.

4. Accessibility

When designing the user interface of the system, we need to consider the needs of different users to meet various preferences and ensure the user-friendliness of the interface.

6.2 Making Recommendations Work for You

In the previous article, from developers' perspective, we discussed the efforts that the recommender system needs to make in order to cater to user preferences and provide users with a better personalized experience. In this section, we will switch perspectives and have a brief discussion from the user's point of view.

In order to get better recommendation results, in addition to rely on the actively collection and analysis of user data through the system, we as users, should understand how to express our needs to the system, so that the recommender system could understands us better and works for us. The active participation of users can help avoid information overload and promote the development of the recommender system.

- Personalization with Purpose

Users are not only recipients of recommendation results, but also contributors to the personalization process. In order to create a better personalized experience, we need to actively express our needs to the system. Wr can manage our preferences purposefully and ensure that the data used by the system is valuable. This not only affects the quality of personalized recommendations, but also helps users control the proportion of relevance and diversity of recommended content, allowing users to find the recommendation model that best suits them.

- Proactively Provide Feedback

When we encounter unsatisfactory recommendation results, we should not accept them passively. In addition to completing the review content provided by the system for users, we can also proactively put forward our own opinions. The more accurate and detailed feedback can help improve the better quality of recommendations. It can not only help increase personal personalized experience, but also assist the recommender system evaluation and promote algorithm optimization, which further contributes to the improvement of user experience for other users.

- **Stay Curious**

We can occasionally accept new opportunities and try out suggestions that go beyond expectations. Based on system recommendations, we can actively view novel items or search for new keywords, which can even turn the recommender system into a tool to help us expand new horizons and learn new knowledge. Users' active exploration can boost the vitality of the recommender system and help its continuous development.

In essence, establishing effective communication between users and the recommender system plays a crucial role in improving the quality of recommendations. The active participation of users enriches the user's position in the recommender system, making users not simply viewers or consumers, but also co-creators of a better recommendation ecosystem.

7. Conclusion and Future Work

Nowadays, the phenomenon of digital flooding on the Internet is very common. Everything from personal cognitive abilities to information characteristics, and to external environmental factors may lead to the emergence of this phenomenon, thus causing a lot of trouble. In order to improve users' online experience, various fields are making efforts to alleviate this phenomenon by using recommender systems. Several representative platforms are leading the way with recommender systems, and their growing user base and annual profits attest to the critical role that recommender systems play. Although the algorithms and functional designs of the recommender systems are different, their overall goal is to improve user satisfaction through better personalized recommendations.

Recommender systems have effectively alleviated the problem of information overload, but if there are not enough considerations when designing the system, it may lead to negative effects. For example, filter bubbles limits users' vision, too much low-quality recommended content brings ineffective information filtering, too many options and confusing information architecture make users lose their sense of control, etc. These factors may cause users to have negative emotions such as fatigue, restlessness and anxiety, and eventually lose trust in the recommender system. To help recommender systems work more effectively, I summarize nine principles and four considerations to help designers find the balance between personalization and information overload to build better systems. I also suggest how we, as users, should get involved when using recommender systems, and work with developers to build positively evolving recommender systems.

In order to achieve positive development of recommender system, one of the major challenges that users face in co-working with the system is how to motivate users to participate in the feedback mechanism. Users often have their own intentions when using the platform. They want to obtain more effective information from the platform at a better cost. In addition to obtaining implicit feedback from users' online behaviors, without sufficient incentive mechanisms, it is difficult for users to spend extra effort to participate in the positive development of the recommender system. An effective solution is to let them feel the results of their efforts very quickly, not just from the next recommendation list, but may also require some clearer immediate feedback or even reward mechanisms. Through this kind of user incentives, users can be more actively involved in user-controlled part of the process, thereby making the recommender system continue to progress in a positive way.

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