A Survey of Explainable E-Commerce Recommender Systems

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Abstract — Since the growing information overload has become more and more serious on the Web, especially in the field of e-commerce. The explainable recommender system plays a crucial role in providing users with explanations of recommendations to enhance customer satisfaction and loyalty. In recent years, various explainable recommender approaches have been proposed and applied in e-commerce. This survey will review the development of explainable recommender systems, existing methods to generate explainable recommendations, applications in the e-commerce field, and further discuss future directions that can be incorporated and implemented to improve the quality of explainable recommender systems.

Keywords—Recommender System (RS), e-commerce.

I. *Introduction*

Nowadays, recommender systems (RS) are deeply involved in people's day-to-day activities, and it supports them in making effective and excellent decisions on time. RS was introduced to provide personalized service or items that are most suitable to particular users. The idea behind personalization is that make individual services available to customers for easy identification of choices from a wide group of choices and meet their desires [1]. In the past few years, there has been a growing expectation of personalized recommendations, especially in the field of e-commerce [2]. Various studies have proved the impact of personalization on revenue increment and improvement in customer satisfaction [3, 4]. To achieve user personalization and predict users' preferences by analyzing users' behavior, RS was widely applied.

However, the majority of RS studies only consider the recommendation quality or the prediction accuracy but did not take into account the reason for recommendations. Developing an explainable RS that can address why an item is recommended. Instead of knowing which products to buy, explanations help users know why products are suggested to buy. Explainability benefits an RS in several aspects: improves the transparency of RS; enhances user satisfaction and trust of RS; helps system maintainers refine the recommendation pipeline on time.

In the past few years, business trading and transaction through e-commerce websites have become the latest standard in the business sector. Performance and price comparisons for products can be carried out on these websites. Improving innovation and service standards to maintain profit in an intensely competitive marketplace is essential for e-commerce. One of the critical factors in the practical realization of this improvement is the incorporation of customer enhancements that aid them in the decision-making process in selecting the products of their interest. Nevertheless, customers are facing difficulties in identifying the most suitable product due to excessive selection and preferences available. To solve the information overload and enhance the stickiness of users and e-commerce websites, a reliable and quality explainable RS is desired and highly essential [5,6,7].

II. *Overview of E-Commerce Recommender Systems*

Since the mid-1990s, the flourishing development of internet, the term "information overload" has caused social anxiety. Both consumers and producers are experiencing challenges: as a consumer, it is very difficult to find interesting items from plenty of products; as a producer, how to make products stand out and attract users' attention, is also a challenge. The recommender system is proposed to solve this contradiction. The RS aims to connect users and information, on the one hand to help users discover products that are valuable to them, and on the other hand to allow products to be displayed in front of users who are interested in it, so as to achieve a win-win situation for consumers and producers. In the late 1990s, e-commerce giants such as Amazon, eBay, and Alibaba launched personalized RS, recommending products to customers based on their characteristics, purchase behavior and product popularity [8].

With the development of the global economy, e-commerce industry has been widely spread in various business fields. Classic examples are digital services and online shopping websites. Most of the existing recommender systems were only focused on improving recommendation accuracy but did not take explainable aspects into account. In fact, many users do not have a clear purchase intention when browsing the website, and are even unfamiliar with certain products, such as investment goods, medicine. Therefore, it is important and necessary for the recommender systems to have the ability to explain.

In order to improve the transparency of the recommender systems, enhance user's trust and acceptance of the recommended products, the explainable framework was officially introduced. We summarize the motivations behind introducing the Explainable RS to users as follows:

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i. Explanation helps system maintainers discover vulnerabilities in a timely manner and refine recommendation pipelines, thereby raising the effectiveness of recommendations [43].
ii. The primary goal of implementing explainable RS in e-commerce is to boost in sales. Compared with recommender systems that are usually not explained, users have a better understanding of recommended products and thus increase user acceptance.
iii. Explanation enhances users' satisfaction by promoting the accuracy of recommender systems. User satisfaction with a recommender system depends on whether the recommended products are interesting and meet their needs.
iv. Explainable RS benefit e-commerce merchants by gaining users' confidence and loyalty. A better personalized service experience earns user trust and subsequently increases the purchase rate. As user loyalty increases, it is easier for the recommender systems to predict user preferences, so that the recommender systems are able to offer recommended products more accurately.

III. Classification of Recommender Systems

Recommender systems are broadly classified into seven types: Content-based filtering RS; Collaborative filtering RS; Hybrid RS; Social Network-based (community based) RS; Demographic Filtering based RS; Knowledge based RS; Computational intelligence-based RS [9].

1) Content-based filtering RS

Content-based filtering RS recommends similar items based on the user's past behaviors and explicit feedback. The primary process behind content-based RS is analyzing features of items purchased by users to determine their preferences. For instance, the content-based filtering book RS will recommend books that have the same author, same publisher, or the same genre as books you purchased before.

The two main techniques employed to generate recommendations are:

- Advanced Machine Learning techniques include decision trees, support vector machines, and Naïve Bayes.
- Traditional Information Retrieval techniques such as Latent Dirichlet Allocation (LDA), Term frequency-inverse document frequency (TF-IDF), and similarity measure.

Content-based filtering RS can only provide recommendations based on users' past interests. In other words, the RS has limited ability to determine what characteristics of items the user currently likes [10].

2) Collaborative filtering RS

Collaborative filtering RS recommends items not only considering the user's historical choices but also connecting users with similar preferences and behaviors. Recommendations are generated by analyzing both explicit and implicit feedback from users. Explicit feedback refers to user ratings for purchasing, while implicit feedback is noticed by users' actions like clicks, searches, purchase history, page views, etc.

Two common techniques are utilized in collaborative filtering RS [8]:

- Model-based algorithms make recommendations by discovering latent user rating characteristics or, conversely, developing a model to predict the preferable item a user may wish to buy [11]. Model-based algorithms consist of Matrix Factorization algorithms that comprise Bayesian networks, tensor factorization, and Restricted Boltzmann machines, amongst others [12].
- Memory-based collaborative filtering techniques provide recommendations based on the selection of nearest neighbor items or users [13]. In other words, users tend to receive recommendations similar to those previously rated in the item-based collaborative filtering technique. whereas the user-based collaborative filtering technique suggests items are based on users that have similar preferences. A previous study confirmed that item-based collaborative filtering performs better than user-based techniques [11].

The Key issue of collaborative filtering RS is Cold-Start. Collaborative filtering systems require a large amount of data from similar users. The cold-Start problem refers to the difficulty to build a brand-new RS without user data.

3) Hybrid RS

A hybrid RS is a mixture of collaborative and content-based filtering RS, which was designed to solve limitations of collaborative and content-based filtering RS, such as the cold-start problem while improving the overall performance. Some approaches were proposed to create hybrid recommender systems: feature augmentation, switching, cascade, metal-level, weighted and mixed features. In most cases, hybrid filtering recommendation techniques are typically based on probabilistic techniques such as genetic algorithms, neural networks, singular value decomposition (SVD), clustering algorithms, and Bayesian networks [14].

4) Social Network-based (community based) RS

Social Networks-based RS employs the information from the social networks to enhance the recommendation accuracy and overcome challenges such as data sparsity and cold-start issues. The social network-based RS revolves surrounding friends having common interests, thereby creating a community-based recommendation model that measures the user's rating similarities [15]. A social network-based recommender system is based on probabilistic approaches such as neural networks and Bayesian networks [16].

5) Demographic Filtering based RS

Demographic filtering-based RS classifies users according to their demographic information such as age, gender, employees, and language. Demographic RS does not require additional knowledge or previous reviews but needs more information, such as textual reviews to improve the accuracy of recommendations [17,18,19].

6) Knowledge based RS

Knowledge-based RS is based on explicit knowledge of how certain product features satisfy customer needs and preferences. The system uses a similarity function to measure how well the recommendations meet the customer's needs. A recommender system is knowledge-based if it is based on a specific query made by a user, rather than on the user's rating history. The system can also ask the user for rules, guidelines, or examples of items that can be used to determine what the search results should look like. The system then searches its database of items and returns similar results [17,20].

7) Computational intelligence-based RS

Computational intelligence-based RS applies machine learning algorithms to predict the users' choices and offer relevant recommendations to users. Some of the intelligent algorithms used for the computational Intelligence recommendation model are genetic algorithms, artificial neural networks, fuzzy set models, and the Bayesian model. The artificial neural network was inspired by a biological brain's structure and can be used to design and implement a model-based recommender system [21].

IV. Explainable Recommendation Models

Explainable RS generally can be categorized into five types: User-based or item-based explainable systems; Social-based explainable systems; Feature-based explainable systems; Review-based explainable systems; Visual explainable systems [10].

1) User-based or item-based Explanation

User-based and item-based explanations are typically provided based on implicit or explicit feedback from users. In user-based collaborative filtering, a set of similar users is first found for the target user. When an algorithm recommends an item to a target user, the user is interpreted as close to a set of "neighboring" users who have rated the recommended item favorably [22]. In item-based explanation, recommendations are similar to items that the user has been interested in or purchased. In general, Item-based explanations are more intuitive to the user [23].

2) Social-based Explanation

Traditional recommender systems usually ignore social interactions between users, so as the target user may not be aware of other users with "similar interests". In fact, users are always turn to their close friends for seeking advice when they are confused with multiple options [24]. If we explain to the user that his/her friends have similar interests in the recommended item, it will be more likely to be believed and accepted. Hence, researchers proposed to combine social network information among users for providing more accurate and personalized recommendations. Social network information refers to the online communication in social media websites between users and their friends. For Instance, Park *et al.* [25] proposed a unified graph structure that uses ratings and social information to generate interpretable product recommendations. Under this framework, recommendations can be interpreted according to users' friends with similar tastes, which can greatly improve user acceptance, user satisfaction, and system efficiency.

3) Feature-based Explanation

Feature-based explanations aims to present reasons intuitively for content-based recommendations, which match features of candidate items with users' preference [26]. Depending on the application scenarios, feature-based explanation can be generated by analyzing features of recommended products. For example, e-book recommendations can be explained based on the genre, price, or author; digital music recommended based on type, singer, or language; clothes recommended based on color, gender, or brand.

4) Review-based Explanation

User reviews continue to accumulate as more and more people get used to expressing their personal opinions on social networks. Past study has proved that user reviews are beneficial for user analysis and accurate recommendations [27]. Furthermore, user reviews help to generate more detailed and reliable explanation for recommendations, so as to facilitate users make more rational decisions [28]. With this motivation, several methods have been proposed to produce explanations based on user-review recommendations.

User-review based explanation approaches can be broadly classified into aspect-level and sentence-level, depending on how the explanation is presented. Aspect-level method generates recommended explanations by extracting the items' aspect, rating, and sentiment from user review texts, whereas sentence-level method tells users items' feature that they might interest in.

5) Visual Explanation

Visual images are generally more direct and easier to understand than text. Visual images are essentially any type of images, videos, and infographics published online [29]. Many users have a great memory for images, they may remember the company logo but not the company name. This inspired researchers to apply object images to produce explainable recommendations. Research on visually explainable recommendations is just beginning. With the advancement of deep image processing techniques, visual images will be integrated into recommender systems for better performance and interpretability.

V. Applications of Explainable Recommender Systems in E-Commerce

Since the beginning of 2020, the outbreak of Covid-19 has been affecting the global economy. In most countries, quarantines and other interventions have limited offline economic activity to protect public health. More and more enterprises are turning to online platforms, leading to a further acceleration in the development of e-commerce. Therefore, explainability becomes a crucial function for recommender systems to stand out among numerous e-commerce retailers. In this section, we present applications of explainable recommender systems in multi-category e-commerce industry. Table 1 shows how explainable e-commerce recommendation studies are classified into different categories.

- Business to Business (B2B) recommender systems:

  Business-to-business refers to commercial transactions between organizations, such as a manufacturer and a wholesaler or retailer. B2B recommender systems recommend internal company products based on the needs of company clients. However, in B2B recommender systems, only positive ratings are available: products have already been purchased. Matrix factorization is often applied to generate recommendations based only on positive ratings. To provide textually, and visually explainable recommendations, Vlachos *et al.* [30] proposed joint clustering on the customer-product purchase matrix to detect common cluster between customers and products. Products in each group that have not been purchased by customers as a candidate set of recommendations. Vlachos *et al.* [31] formulated co-clustering approach to identify set of customers that are interest in set of products. Previous studies indicates that enterprises in B2B market do not have a deep understanding of customer needs. To improve customer satisfaction and loyalty, Tarnowska *et al.* [32] presented a knowledge-based recommender system by analyzing aspect-based sentiment from customer comments.

- Business to Consumer (B2C) recommender systems

  Business-to-consumer (B2C) is a digital sales form between a company and consumers. Many of largest commerce website and software companies employed recommender systems to provide personalized digital products (music, movie, etc.) and physical goods (books, clothes, medicine, etc.).

  The popularity of digital products (music, movie, etc.) has exploded with the dramatic increase in the number of downloads and related software. Users are no longer limited to only focusing on certain singers or actors but are moving towards selecting songs and movies based on genres, emotions, and other categories. The website or software recommends personalized playlists that meet the user's interests based on their browsing history and preferences. Zhao *et al.* [33] aims to make users feel like recommended music come from friends by extracting explainable recommendation reasons from music comments. For example, the recommended song named "*I love you but goodbye"*, while recommendation reason: "Every time I listen this song, I think of my first love". To enable explainable recommendation of Amazon Instant Video, Zarzour *et al.* [34] introduced a trust collaborative filtering model to encourage users to accept recommended films by presenting five elements: recommended item, active user, predicted rating, number of users sharing the same preferences with the active user, and the average trustworthiness. Ghazimatin *et al.* [35] explored PRINCE (Provider-side Interpretability with Counterfactual Explanations) for digital music and movie recommendations aimed at discovering minimal users' actions (purchases, ratings, and reviews) that influence recommendations.

Explainable personalized recommender systems are most widely adopted on retailer websites. Zhang *et al.* [36] proposed the Explicit Factor Model (EFM) to generate intuitional feature-level recommendation explanations for JD commercial website by analyzing explicit product features and user reviews. He *et al.* [37] devised TriRank (tripartite graphs ranking) algorithm to provide explainable recommendations on Amazon Electronics. Moreover, there are few studies attempted to use deep learning method to generate explainable recommendation for e-shopping RS. For instance, Ai *et al.* [38] employed soft matching algorithm with knowledge-based embeddings framework to provide explainable recommendations on Amazon datasets; Lin *et al.* [29] developed a gated recurrent neural network (RNN) with a cross-modality attention mechanism to generate abstractive explanations for Polyvore fashion outfit recommendations; Zarzour *et al.* [39] extracted ratings and reviews from Amazon as input of LSTM model to clarify why products are suggested to buy; Wu *et al.* [40] adopted a novel CARL (context-aware user-item representation learning) with an attention model to conduct explainable recommendations for Amazon; Chen *et al.* [41] introduced a multimodal attention neural architecture for fashion recommendations based on both image region-level features and user reviews.

VI. *Evaluation Methods of E-Commerce Recommendation Explanations*

Methods of e-commerce recommendation explanations are usually be evaluated from three main perspectives: whether the explanations help users to make more accurate and faster decisions; whether the explanations can improve the transparency of recommender systems; whether the explanations will persuade users to accept recommendations. Evaluation methods are broadly categorized into four types: user study; quantitative metrics; online evaluation; offline evaluation [42][43].

- User Study

  User study-based evaluation is to recruit volunteers or paid experiment subjects. Researchers will design a group of related questions for subjects to complete and then conclude experimental results from subjects' responses. Dominguez *et al.* [44] designed a visual content-based recommender system for online web store *UGallery*. To evaluate the recommendation explanations, a user study in Amazon Mechanical Turk was conducted. Participants were asked to complete a survey to rate on scale of 0 (totally disagree) to 100 (totally agree) how likely they would understand the recommendations. User studies enable researchers to analyze in depth by designing more complex questions. However, participants' responses may be biased since they know they are being observed.

- Quantitative metrics

  With the increasing employment of machine learning techniques in recommender systems, researchers have explored many quantitative metrics to evaluate ML-based recommendation explanations, for instance, BLEU and ROUGE scores, Unique Sentence Ratio (USR), Feature Coverage Ratio (FCR), Feature Diversity (FD), Feature-level Precision (FP), and so on. Li *et al.* [45] proposed a recommender system for Amazon Movie & TV. To evaluate the performance of recommendation explanations, BLEU and ROUGE scores, Unique Sentence Ratio (USR), Feature Matching Ratio (FMR), Feature Coverage Ratio (FCR), and Feature Diversity (DIV) were adopted.

- Online evaluation

  Unlike user study-based evaluation, participants know they are being investigated. Online evaluations are usually conducted without participants' awareness of the investigation. The online evaluation will test the recommendation explanation by collecting traceable user behaviors in the test environment, such as calculating the purchase rate of participants with and without recommendation explanation. Zhang et al. [46] issued an online test for a shopping website to evaluate the performance of recommendation explanations by comparing the users' click-through rate with or without explanations. Online evaluation is less flexible as it can only be performed based on limited user behaviors in the test environment.

- Offline Evaluation

  Offline evaluation of explained recommendations is done using a historical dataset during a period. Zhang et al. [42] proved that offline evaluation usually is conducted with text-based measures. For example, on many online shopping websites, users' historical reviews of an item are the recommendation explanation for other users. The textual generation metrics, such as BLEU and Rouge score are utilized to evaluate the performance of explanations. However, the offline explanation evaluation would be challenging if historical datasets are unavailable.

VII. *Future Research Directions*

In this work, we review the development explainable recommender systems, applications in e-commerce industry. Even though applications on explainable recommender systems have made great progress in recent years, there are still some challenges that require further research.

1) The recent spread of e-commerce has promoted the application of recommender systems in various business activities, such as government-to-consumer (G2C) recommender systems. The G2C recommender systems usually provide non-profit public service. Different from common e-commerce systems, government services not only involve personal privacy but also social security, so it is relatively difficult to explain the reasons for recommendation. These factors should be considered in future research on G2C recommender systems.
2) In the field of e-shopping, user behavior and interests are constantly changing. Using real-time data to predict users' current preferences will be challenging. To predict user preferences and improve recommendation accuracy in a rapidly changing network environment, Gama et al. [47] proposed a concept drift technique to model user preference changes. Combining concept drift techniques with recommender systems will be an emerging research topic [48].

3) Most e-commerce managers care more about short-term profits, and rarely realize that a good recommendation experience will have cumulative value for user retention. The better explanation experience of the recommender systems enhances the user's trust and loyalty. However, this improvement requires a lot of testing and additional development costs. Therefore, the development of simple and low-cost explainable recommender systems is still a worthwhile direction.

4) The existing recommendation explanations tend to be generic. Although recommender systems can give explanations based on users' behavior, there is still a huge gap between current explanations and interactive recommendation explanations. With the development of NLP technology and voice interaction, future recommender systems will be able to generate flexible and emotionally intelligent explanations in the process of interacting with users.

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Table 1: classification of e-commerce explainable recommendation methods. The classification is based on two dimensions: the types of e-commerce; the methods of the generated explanation.

	Methods of Explainable Recommendation		
Categories of e-commerce / explanations	Business to Business	Digital products	e-Shopping retailers
User-based or Item-based	Vlachos *et al.* [30] Vlachos *et al.* [31]		
Social-based		Zhao et al. [33]	
Feature-basd			Zhang et al. [36] Ai et al. [38] He et al. [37]
Review-based	Tarnowska et al. [32]	Ghazimatin et al. [35] Zarzour et al. [34]	Zarzour et al. [34] Wu et al. [40] Chen et al. [41] Lin et al. [29]
Visual-based			Chen et al. [41]