Enabling Intelligent User Control in AI-Driven Recommender Systems

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Abstract

User controllability is an important issue in recommender systems, and there are different approaches to facilitate user control through various types of interactions with recommender systems, as in knowledge-based recommender systems, conversational recommender systems, and visual interactive recommender systems. Recent developments of AI-driven recommender systems calls for intelligent mechanisms and user interfaces for smart user controllability. Our experiences developing mechanisms for smart user control led to discussions highlighting the importance of regulating AI-driven recommender systems at a meta level and providing intelligent user interfaces for user controllability.

Keywords

Recommender systems, Large language models, Intelligent controllability, Intelligent explainability

1. Introduction

In the era of information overabundance, recommender systems [1] have become a primary means through which people navigate digital content. Traditional recommender systems draw on content-based approaches, which match item attributes with user profiles, collaborative filtering approaches, which exploits patterns among similar users or items, or hybrid approaches, each with different properties in terms of explainability and controllability. More recently, the rapid advancement of deep learning and large language models has given rise to a new generation of AI-driven recommendation algorithms [2]. While collaborative filtering and AI-driven approaches rank among the most powerful recommendation techniques, their black-box nature makes it inherently difficult for users to understand why certain items are recommended or to steer recommendations toward more relevant and desirable ones.

User controllability is an important issue in making recommender systems trustworthy [3]. There are different approaches to facilitate user control through various types of interactions with recommender systems, as in knowledge-based recommender systems, which match user requirements with the attributes and rules of a specific domain, conversatioal recommender systems, which clarify user preferences and make suggestions through dialogues, and visual interactive recommender systems, which use interactive visualization to explore and refine recommendations.

Recent developments of AI-driven recommender systems calls for intelligent mechanisms and user interfaces for smart user controllability. Our experiences developing mechanisms for smart user control led to discussions of co-pilot recommendation framework involving a meta-design tool, highlighting the importance of regulating AI-driven recommender systems at a meta level and providing intelligent user interfaces for user controllability. Rather than focusing solely on improving accuracy, advanced AI can be leveraged to build *intelligent user interfaces that enhance the explainability and controllability* of recommender systems.

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2. User Controllability in Interactive Recommender Systems

We next discuss existing approaches to user controllability in interactive recommender systems, including the ones in knowledge-based recommender systems, conversational recommender systems, and visual interactive recommender systems. Beyond standalone use, these approaches can serve as the building blocks for hybrid approaches.

2.1. Knowledge-Based Recommender Systems

Knowledge-based recommender systems use knowledge about users and products to pursue a knowledge-based approach to generating a recommendation, reasoning about what products meet the user's requirements [4]. They typically employ either constraint-based or case-based approaches. Unlike content-based and collaborative filtering-based recommender systems, knowledge-based recommender systems consider user inputs during the recommendation process and can support "cold-start" recommendation scenarios in the absence of extensive historical data (e.g., recommending cars, houses, and other expensive items that people do not buy frequently.) Interactive recommendation processes in knowledge-based recommender systems provide users with the opportunities to revise and/or critique requirement specifications until users can obtain satisfactory recommendation results. Such interactive processes can *foster a sense of self-directed discovery, thereby improving user satisfaction*. However, designing kowledge-based recommender systems can be sometimes challenging because of the need to define item features, constraints and/or similarity models, etc. using relevant domain knowledge.

2.2. Conversational Recommender Systems

Conversational recommender systems (CRS) [5] exploits conversational interactions to provide relevant recommendations. The interest in CRS has significantly increased in the past years mainly due to the progress in natural language processing, voice-controlled home assistants, and chatbots.

Users can control their recommendations through natural language interaction with the system. Moreover, conversational interactions can help the system to *elicit preference information* from users or allow users to ask questions about the recommendations and to *give feedback*. CRS can be used in various recommendation scenarios including tourism recommendation [6].

2.3. Visual Interactive Recommender Systems

We can also exploit visual representations to facilitate users' interactions with recommender systems. CourseQ is a course recommendation system for university students, which integrates interactive visualization and recommendation techniques to help the *explanation and exploration* of the recommendation processes through an interactive interface [7]. The visually-based interactive approach we employed with the CourseQ system improved perceived recommendation accuracy, as well as user satisfaction with the course recommendation system for university students. He et al. discuss an interactive visualization framework that combines recommendation with visualization techniques to support human-recommender interaction [8]. Jin et al. discuss a visual user interface for music recommendation with different controls including interactions with the output of a recommender system, user profiles, and weights in an recommendation algorithm [9].

3. Smart User Controllability

We next discuss how intelligent mechanisms could be used to provide a means of effective control in advanced recommender systems. In particular, our recent developments [10, 11, 12] suggest the potential for providing *smart user controllability* for recommender systems. *Smart user controllability* can facilitate users' process to interact with recommender systems by providing intelligent user interfaces that are explainable and efficiently controllable.

3.1. Improving Explainability in Deep Learning-based Recommendation

Explainability is a critical property of interactive recommender systems, as it helps users to understand *why* items are recommended. Explanations generally help improve the effectiveness, efficiency, persuasiveness and user satisfaction of recommender systems [13]. In interactive recommender systems, it can help users meaningfully control the recommendation processes. However, the degree of explainability varies considerably across recommendation models. Widely used collaborative filtering (CF) models and recent deep learning-based models are inherently low in explainability, making it difficult to provide users with effective control mechanisms without the development of dedicated explainability techniques.

Based on an extensive discussions on explainability in educational course recommendation systems [14], we have proposed a deep learning-based recommendation model with the built-in capability to enhance explainability by leveraging knowledge graph information [12]. Our experimental results show that we can simultaneously improve explainability and accuracy of recommendation. Improving explainability in such a way is a key step towards supporting meaningful control of deep learning-based recommendation processes.

3.2. Diversity Tolerance for Personalized Control of Recommendation

Recommender systems tend to prioritize content that matches users' historical behaviors. This can cause problematic situations such as "filter bubbles." We can of course intentionally diversify recommendation by mixing some items that do not match the user's historical behaviors. However, this approach of course can easily affect recommendation accuracy, and thus there is the need to address the trade-off between recommendation accuracy and diversity.

The optimal balance within this trade-off may vary from user to user. For example, recommending movies in different genres can be acceptable for casual movie watchers. However, it can be less acceptable to do so for people who watch sci-fi movies only. We operationalized this issue by introducing so-called *diversity tolerance* metric and used it to provide diversified recommendations by considering individuals' *diversity tolerance* score [10]. The score can be computed based on historical data about users' interactions with items as well as knowledge graph data that enriches item information (see Figure 1). This mechanism has achieved statistically significant improvements in recommendation diversity while maintaining competitive accuracy compared to state-of-the-art baselines. As such, the mechanism can be useful for developing intelligent user interfaces that adapt to individuals' tolerance for diversity considering the accuracy-diversity trade-off.

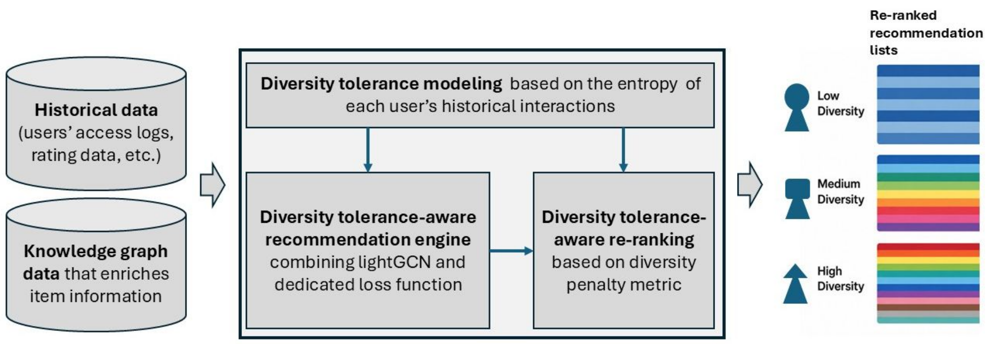

Figure 1: A recommendation mechanism based on *diversity tolerance* [10]. Historical data and knowledge graph data can be used to model diversity tolerance for each user and thereby producing the recommendation lists that suit users' different diversity tolerance.

3.3. Topic-wise Controllable Diversification

Researchers have proposed various techniques for increasing the diversity of recommended items to remedy this problem. However, existing techniques often diversify recommendation in simplistic manners, without fully considering different dimensions along which recommendation can be diversified.

To address this limitation, our research group has proposed *topic-wise controllable diversification mechanism* for recommender systems [11]. This mechanism allows system designers and/or users to control the distribution of recommended items along different topic dimensions (see Figure 2). By integrating topic modeling and attribute labeling, the pipeline minimizes the manual effort required for users to identify key dimensions and define their corresponding values. For example, in news recommender systems, topics can be used to represent different social issues. Users can then enact fine-grained control of news recommendation by adjusting the diversity of viewpoints or stances for each topic. This work has suggested the feasibility of creating usable and useful user interfaces for enacting fine-grained control over recommendations by employing an intelligent modeling and processing framework. Unlike existing recommendation mechanisms that use machine intelligence to increase accuracy, we can use it to provide intelligent user interfaces that facilitate effective user participation in the recommendation process with minimum burden on users.

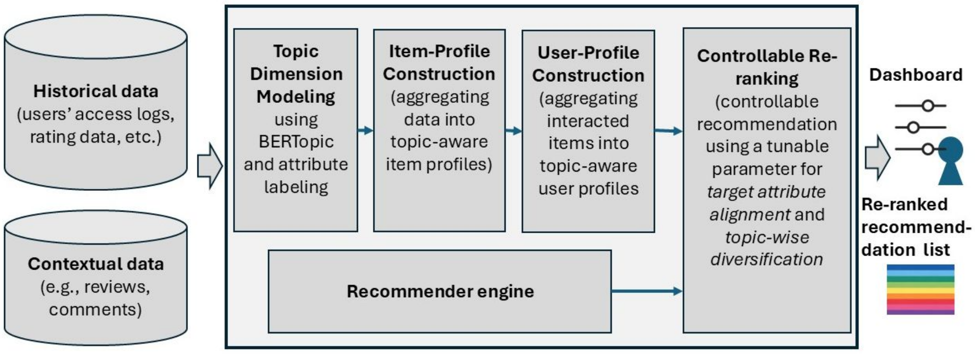

Figure 2: A recommendation mechanism with topic dimension-wise controllability [11]. Leveraging historical and contextual data to model topic dimensions and profiles enables granular, topic-based control over recommendations via a dashboard interface.

4. Discussion

4.1. Intelligent Support for Regulating Recommendation at a Meta Level

There has been an increasing interest in deep learning-based and generative AI-based intelligent recommender systems [2]. Researchers have exploited intelligent AI capabilities in various ways to enhance the capabilities of recommender systems.

As we described in the previous section, we have modeled *diversity tolerance* to regulate the diversity of recommendation results by predicting how much diversity in recommendation each user may accept. Our experience with this approach suggests a potential of AI models to support users' interactions with recommender systems at different levels. Instead of using machine intelligence to recommend items directly, we have used it to predict *diversity tolerance*, which is contextual information for regulating recommendation at a meta level. By predicting such contextual information and facilitating user control over recommendation, we can allow users control recommender systems while minimizing user effort.

4.2. Intelligent User Interfaces for User Controllability

With the topic-wise controllable diversification, users can specify their preferences with a small number of meaningful topic dimensions, thereby making the task of performing fine-grained control over recommendation easy. Our experience with the topic-wise controllable diversification mechanism suggests the potential of *employing AI to provide an intelligent user interface for usable and useful control* over recommendation. The mechanism partially automates the process of modeling and selecting important topic dimensions for user control, and these topic dimensions serve as a basic information model for instantiating intelligent user interfaces enabling fine-grained control over recommendation with minimum user effort. The topic dimensions define the medium for user-system communication, and they are derived dynamically based on the data with some help from users. Intelligent user interfaces based on such topic dimensions can support user participation and control in recommender systems while maximizing its effectiveness and minimizing user efforts. Overall, our exploration with the mechanism suggests the potential of AI models to provide user-friendly intelligent user interfaces for user controllable recommendation, enabling close-knit synergy of users and recommender systems.

4.3. The Co-Pilot Platform

By integrating and extending the techniques we developed to improve controllability and explainability of recommender systems, we propose a recommendation co-pilot platform involving the steering UI to modify the states of the control objects for regulating the behaviors of the recommendation engine (see Figure 3. Examples of control objects include *diversity tolerance* specification and topic dimension-wise specifications, and they can be added, removed, and/or modified via an intelligent design tool. The co-pilot platform extends recommender engine toward a more holistic recommendation platform by introducing the intelligent design tool for supporting *meta-design* [15] as well.

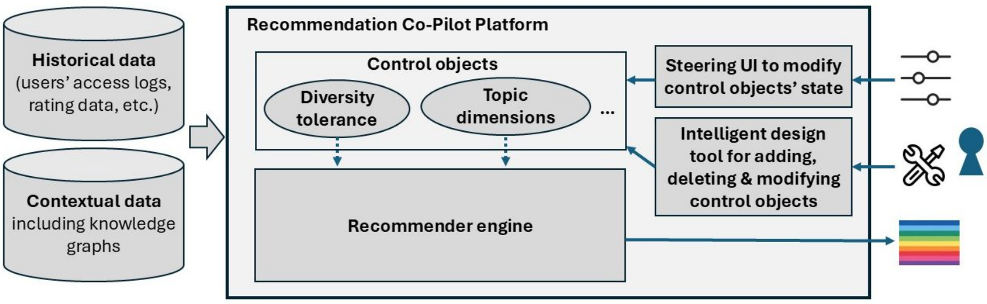

Figure 3: Conceptual illustration of a recommendation co-pilot platform. Users can control the recommender engine by changing the state of control objects through the steering UI. They can also add, delete and modify control objects using the intelligent design tool.

5. Conclusion

User controllability is an important issue in recommender systems, and there are different approaches to facilitate user control through various types of interactions with recommender systems. Recent developments of AI-driven recommender systems calls for intelligent mechanisms and user interfaces for smart user controllability. Our experiences developing mechanisms for smart user control led to the discussions of intelligent support for regulating recommendation at a meta level, intelligent user interfaces for user controllability, and the co-pilot platform involving intelligent tool for supporting meta-design. Future developments of the co-pilot platform can be informed by the discussions of Distributed Cognition and Symbiotic AI [16] as well.

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Declaration on Generative AI

During the preparation of this work, the author used sonnet-4.6 and Gemini 3 in order to: Grammar and spelling check. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

References

[1] C. C. Aggarwal, Recommender Systems: The Textbook, Springer, Cham, Switzerland, 2016.

[2] Z. Zhao, W. Fan, J. Li, Y. Liu, X. Mei, Y. Wang, Z. Wen, F. Wang, X. Zhao, J. Tang, Q. Li, Recommender systems in the era of large language models (llms), IEEE Trans. on Knowl. and Data Eng. 36 (2024) 6889–6907. doi:10.1109/TKDE.2024.3392335.

[3] Y. Ge, S. Liu, Z. Fu, J. Tan, Z. Li, S. Xu, Y. Li, Y. Xian, Y. Zhang, A survey on trustworthy recommender systems 3 (2024).

[4] R. Burke, Knowledge-based recommender systems, in: A. Kent (Ed.), Encyclopedia of Library and Information Science, volume 69, CRC Press, 2000, pp. 181–201.

[5] D. Jannach, A. Manzoor, W. Cai, L. Chen, A survey on conversational recommender systems, ACM Comput. Surv. 54 (2021). doi:10.1145/3453154.

[6] Y. Liu, Bayesian Optimization-Based Preference Elicitation with Large Language Models Conversational Tourism Destination Recommendation, Master's thesis, Kyushu University, 2026.

[7] B. Ma, M. Lu, Y. Taniguchi, S. Konomi, Courseq: the impact of visual and interactive course recommendation in university environments, Res Pract Technol Enhanc Learn 16 (2021). doi:10.1186/s41039-021-00167-7.

[8] C. He, D. Parra, K. Verbert, Interactive recommender systems: A survey of the state of the art and future research challenges and opportunities, Expert Systems with Applications 56 (2016) 9–27. doi:https://doi.org/10.1016/j.eswa.2016.02.013.

[9] Y. Jin, N. Tintarev, K. Verbert, Effects of personal characteristics on music recommender systems with different levels of controllability, in: Proceedings of the 12th ACM Conference on Recommender Systems, RecSys '18, Association for Computing Machinery, New York, NY, USA, 2018, p. 13–21. doi:10.1145/3240323.3240358.

[10] B. Ren, T. Yang, B. Ma, S. Konomi, Leveraging personalized diversity level for recommendations with knowledge graph, Journal of Intelligent Information Systems (2025). doi:10.1007/s10844-025-01013-8.

[11] T. Zhang, A Topic-Aware Recommendation Framework for Controllable Exposure), Master's thesis, Kyushu University, Fukuoka, Japan, 2026.

[12] T. Yang, B. Ren, C. Gu, B. Ma, T. He, S. Konomi, Towards better course recommendations: Integrating multi-perspective meta-paths and knowledge graphs, in: Proceedings of the 15th International Learning Analytics and Knowledge Conference, LAK '25, Association for Computing Machinery, New York, NY, USA, 2025, p. 137–147. doi:10.1145/3706468.3706486.

[13] Y. Zhang, X. Chen, Explainable recommendation: A survey and new perspectives, Foundations and Trends in Information Retrieval 14 (2020) 1–101. doi:10.1561/1500000066.

[14] B. Ma, T. Yang, B. Ren, A survey on explainable course recommendation systems, in: Distributed, Ambient and Pervasive Interactions, Springer Nature Switzerland, Cham, 2024, pp. 273–287.

[15] G. Fischer, D. Fogli, A. Piccinno, Revisiting and Broadening the Meta-Design Framework for End-User Development, Springer International Publishing, Cham, 2017, pp. 61–97. doi:10.1007/978-3-319-60291-2_4.

[16] G. Desolda, A. Esposito, R. Lanzilotti, A. Piccinno, M. F. Costabile, From human-centered to symbiotic artificial intelligence: a focus on medical applications, Multimedia Tools and Applications 84 (2025) 32109–32150.