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# *The Impact of Feedback Mechanisms on Strategy Optimization in Recommender Systems*

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***Abstract.*** With the increasing problem of information overload, recommenders are essential on many websites to help users find interesting content quickly. User feedback is the most valuable form of model feedback, and the form and how user feedback is used affects the accuracy, coverage and experience of recommendations. Thus, this paper reviews feedback types in recommender systems: explicit, implicit, and deliberate implicit feedback, and discusses their pros and cons in terms of accuracy, ease-of-use, and user effort. Additionally, it discusses challenges recommendation models face when using feedback, like data sparsity, bias reinforcement, and fairness limitations. Meanwhile, it proposes strategies to address these challenges by integrating multi-source feedback, fairness-aware modeling, and interpretability enhancement to boost user confidence. The results show gains in accuracy, coverage, and fairness. In addition, it provides exploratory analyses on dynamic feedback and cross-domain recommendations, offering insights for modeling and applying multi-type feedback in future recommender systems.

***Keywords:*** Recommender systems, user feedback, fairness, interpretability, user experience

## 1. Introduction

In e-commerce, social media, and content platforms, recommender systems deliver tailored services through information filtering and content recommendation [1,2]. With technological advancements, recommendation approaches have advanced from the neighborhood-based collaborative filtering to model-based methods and ultimately to deep learning- and reinforcement learning-based intelligent recommendations. Throughout this progression, user feedback has remained the key data source for model learning. Initially they were explicit ratings, followed by implicit behavioral data, and later deliberate implicit forms providing progressively more informative feedback to predict and explain user feedback. Despite considerable success in improving accuracy and addressing sparsity and hybrid feedback models, challenges still remain in fairness, interpretability, user experience, and dynamic feedback modeling. These challenges result in recommendation bias, poor exposure of long-tail items, and lower user engagement in practical applications [3,4]. Therefore, this paper explores the influence of multiple types of user feedback mechanisms in recommender systems, focusing on how different feedback types drive model performance and examining strategies for integrating multi-source feedback to mitigate data sparsity and bias. Furthermore, it is examined how these properties can be introduced into the modeling process. Through the review and synthesis

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of the related studies, it is aimed that some theoretical and practical suggestions can be provided for the recommenders functioning in complex and dynamic feedback environments, and it is tried to present the strategies that increase the performance of the system, improve the user experience, and provide more fairness and interpretability.

## 2. Types and attributes of feedback mechanisms

### 2.1. Features and applications of explicit feedback

Explicit feedback contains users' explicit feedback on items or services they have consumed, e.g., purchasing items on e-commerce websites and assigning 5-star ratings, and clicking "like" or "favorite" buttons on social media [5,6]. Compared with implicit feedback, the explicit feedback indicates users' clear preferences, which is much more semantic, informative, and easy to interpret. Specifically, a user giving a five-star rating to a movie indicates explicit user satisfaction, while a user liking an article just gives a positive appraisal. In this way, the explicit feedback provides high quality and interpretable supervision for the recommendation model to better learn user preferences and improve personalization and user experience.

However, advantages of explicit feedback also have some limitations. Firstly, the collection of explicit feedback is based on the active participation of users. As most users rarely rate or give feedback, data sparsity will be a significant problem [7]. Secondly, users' rating standards may vary greatly, which leads to different levels of evaluation reliability. Explicit feedback has a limited coverage since it cannot reflect users' deep interests. In practice, explicit feedback needs to be used together with implicit or hybrid feedback to complement its limitations and take advantages.

### 2.2. Features and handling of implicit feedback

Implicit feedback is the behavioral signal that naturally exists in the process of users interacting with the system, such as clicks, stay time and purchase history. In contrast to explicit feedback, users do not need to take deliberate action to express their preference for items, but implicitly feed back their preference to the system based on their behaviors. Recently, the implicit feedback can be further classified into unintentional implicit behavior and deliberate implicit feedback. The latter appears when users deliberately perform some behaviors (e.g. click on items with different types) to influence the future recommendation, and they expect to get more diversity or novelty. This make both challenges and opportunities for designing recommender systems.

The advantages and disadvantages of implicit feedback. Implicit feedback is easy to collect, because it exists in the process of users using the system. Compared with explicit feedback, implicit feedback contains more behaviors, makes the data more complete, reduce the sparsity, and provides more behaviors for the training of models. However, implicit feedback also has disadvantages. User behavior is not necessarily express their real preference, which means click not necessarily express their real preference, and not click does not necessarily express no preference. In addition, due to the inherent noise of implicit feedback and lack of explicit negative samples, the problem of model training and evaluation also exits. Matrix factorization methods capture latent relationships between user behaviors and items, while deep learning models use multiple behavioral features to capture complex preferences. Besides, mechanisms that assign weights or adjust confidence for different behavioral types help mitigate the impact of noise, thus enhancing the efficiency of implicit feedback utilization and improving predictive accuracy in recommender systems.

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### 2.3. Mechanisms and design of hybrid feedback

Hybrid feedback refers to the joint use of explicit and implicit feedback in recommender systems to improve model performance. For example, the combination of explicit ratings or likes with implicit behaviors, like clicks, browsing, or purchases, forms a hybrid feedback framework. This approach compensates for the shortcomings of single-type feedback: explicit feedback provides high-quality semantic signals, while implicit feedback contributes abundant, wide-coverage data. The integration of both boosts prediction accuracy, as well as coverage and robustness [8,9].

For hybrid modeling, several fusion mechanisms have been designed. Among them, attention mechanisms set different weights on explicit and implicit features and make the model focus on the most valuable signals for prediction. Also, by optimizing rating prediction and behavior-sequence modeling in a concurrent way, multi-task learning explores complementary information existing in the two kinds of feedback types. In addition, feature transformation, normalization and weighting strategies can mitigate distributional inconsistency and redundancy, and enhance the integration effect in practice.

However, hybrid feedback also brings new challenges to recommendation tasks. Higher feature dimensionality and increased computational cost may decrease training efficiency. Different feedback types are associated with different impacts, and the selection of weighting and fusion strategies has significant influence on the performance of models, which need to be tuned carefully. Meanwhile, noises in feedback are still existing and may still affect the final prediction, especially in large-scale systems. Therefore, integrating hybrid feedback efficiently, scalably and robustly is still an important issue in recommender systems research.

## 3. The influence of feedback mechanisms on recommendation models

### 3.1. Feedback types and model performance

By using different types of user feedback, recommendation models can capture various levels of information [5,8]. Explicit feedback provides clear signals that directly reflect user preferences, making it particularly effective for improving recommendation accuracy and short-term predictions. In contrast, implicit feedback, derived from behavioral sequences such as clicks, dwell time, browsing paths, and purchase history, reveals latent patterns and long-term preferences, helping models understand users' evolving interests.

Models can benefit from both explicit and implicit feedback since each type of feedback has its own advantages. In , Joint Neural Collaborative Filtering (J-NCF) firstly learn both explicit ratings and implicit behavioral sequences explicitly and implicitly respectively by deep neural networks. In this model, explicit feedback helps to learn accurate preference while implicit feedback helps to learn regular behavior. Finally, the precise preference and regular behavior are integrated together by J-NCF and learn comprehensive user and item representation through above joint learning mechanism. The experimental results on MovieLens and Amazon datasets show that, compared with models based on single type of feedback, J-NCF gets significant improvement on Hit Rate (HR) and Normalized Discounted Cumulative Gain (NDCG) [8, 9]. These performance improvement comes from the complement of feedback signal: explicit feedback can provide fine-grained item preference information while implicit feedback can learn user behavior trend and possible interest. For example, when user rating is very sparse, implicit feedback can still provide rich information to learn. Thus, the joint learning can bring improvement on both short behavior and long behavior, and then improve the precision of prediction and user experience on all aspects.

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### 3.2. Feedback bias and its impact on fairness

Feedback mechanisms bring bias and fairness issues into recommenders. A few typical examples are popularity bias, in which popular items are favored due to their high click/frequency or rating events; and feedback loops, in which users' feedback on recommendation results reinforces the pre-existing bias. These two types of bias emerge from data imbalance and self-reinforcing training mechanism. More feedback from popular items leads to more preference to popular items, while

To mitigate bias and enhance fairness, several approaches have been proposed [3]. The Causal Adjustment for Feedback Loops (CAFL) models causality to mitigate bias amplification in feedback loops. In addition, the Bias-Aware Fairness in Recommender Systems (B-FAIR) method mitigates bias by adding fairness constraints to variational autoencoders that model user-item exposure. Feature-independent fairness frameworks further remove bias towards attributes labeled as sensitive, e.g., race or gender. Previous studies have demonstrated that CAFL eradicates popularity bias, B-FAIR improves fairness between groups, and feature-independent methods improve fairness for sensitive attributes. These fairness enhancements, however, come at the expense of increased computational cost, reduced scalability, and small improvements in recommendation accuracy under fairness constraints.

### 3.3. User interaction and experience impact

Feedback can impact model accuracy as well as user experience and engagement. Explicit feedback (ratings, likes, comments) takes time and cognitive effort, and may be burdensome if users are repeatedly asked to provide it; this may decrease engagement and harm recommenders on sites where users frequently interact or on a large scale.

In contrast, implicit feedback is collected implicitly through users' natural interactions. For example, clicks and dwell time track user interest, scroll position indicates engagement with items shown, and purchases indicate interest in recommended items. This requires no effort from the user, but is opaque because the user may not be aware that clicks, scroll position, or purchases impact recommendations and thus harms trust and fairness. Recommenders are moving towards being more explainable (making clear how a recommendation was caused or influenced by past behaviors such as making past relevant content salient, being confident about recommendations, and providing short natural language justifications) or more interactive (providing more control and satisfaction by letting the user update their preferences, giving relevance feedback, or specifying the ranking constraints of items). Even more interactive are recommendation interfaces that show social signals such as what other users have rated or bookmarked; these encourage exploration and are even more fun [8,10]. By combining the best of both explicit and implicit feedback and making it transparent and interactive, we can build recommenders that are both fun and trustworthy.

## 4. Recommender strategy optimization and future directions

### 4.1. Model design and training optimization

Future recommender models should incorporate various types of user feedback more effectively [5,6]. Typical solutions are multi-task learning, weighted loss functions, and attention mechanisms [9]. In particular, multi-task learning forces the model to make predictions for several related tasks simultaneously, thus promoting the use of complementary information and mitigating the sparsity problem associated with a single type of feedback. Weighted loss functions place more emphasis on

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different types of feedback, which helps to alleviate the impact of noisy data and promote use of high-quality inputs. Attention mechanisms allow the model to adjust the contribution of different types of feedback during prediction, with more emphasis on the most informative signals, which leads to improved performance [9].

According to previous research, models that apply multiple tasks learning and attention-based fusion of explicit and implicit feedback of users get significantly increase in Hit Rate and Normalized Discounted Cumulative Gain (NDCG) on MovieLens and Amazon [5]. Besides, they are much more effective for dealing with data sparsity and noise. Therefore, the use of multiple feedback signals can improve the predictive accuracy and serve as an optimization layer in practice for recommender systems.

### 4.2. Feedback integration and interpretability

In addition to being more accurate, recommender systems should also be interpretable to increase transparency, trust, and controllability. Although conventional models are highly accurate in prediction, they cannot explain why certain items are recommended, which may decrease users' trust on the system and make it hard to control its behavior. Various methods have been proposed to improve interpretability either at system level or on specific models. Visual explanation interfaces provide graphical or highlight explanations to reveal the connections between recommended items and users' previous interactions, which makes the recommendation process more understandable. Explanation modules append natural-language or symbolic descriptions to explain how explicit ratings and users' implicit behaviors contribute to the recommendations. By revealing the confidence level, the system supports users to understand the recommendation result and make a decision to trust it or not. For feedback-fusion models, either implicit signals or explicit signals can be injected by weighting or applying an attention mechanism, and the above three types of feedback's contribution can be visualized for the user to understand how each feedback impacts on the recommendation. These interpretable designs enhance users' trust, engagement, and perceived control, which further benefit the user's long-term engagement with and satisfaction on the system.

### 4.3. Data governance and future directions

Future feedback recommender systems have to confront with some problems actively. Feedback loop and data sparsity: use causal inference, group fairness constraints or feature independent frameworks to solve popularity bias problem and make long tail items and minority user group be revealed [4,8]. For long-term value, there is an increasing trend towards recommender system research beyond short-term metrics like click-through rate, and maximizing user satisfaction and system value becomes the main goal. Reinforcement learning and multi-objective optimization techniques are applied to estimate and maximize user lifetime value (LTV). Moreover, by incorporating modern AI architectures like large language models (LLMs), graph neural networks (GNNs), or reinforcement learning agents, recommender systems have a powerful way to model the multi-source data and behavioral dynamics. These methods bring high quality, interpretable and multimodal understanding. Recommendation based on deliberate implicit feedback is another research direction. By detecting purposeful user behaviors, i.e., explorative clicks or deliberate ratings, recommender systems can understand user behaviors better and improve recommendation. New challenges emerge with these advancements. Introducing fairness constraints and combining large models raise computational and storage costs, optimizing long-term value relies on accurate user lifecycle behaviors modeling. Data sparsity and feedback noise are still big issues. Moreover,

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detecting and modeling deliberate implicit feedback requires sophisticated behavior analysis and system design.

## 5. Conclusion

In this paper, the impact of using user feedback signals in recommendation systems is studied. It is found that explicit feedback, although providing rich signals of user preferences, is plagued by data sparsity and high labeling costs; while feedback signals collected implicitly (e.g., clicks) are easier to collect, they are often noisy and possibly reflect preferences different from the user's true preference, and thus require extra modeling and calibration; a new type of feedback signals, deliberate implicit feedback, captures user behaviors that are often hard to model (e.g., exploration or exploitation), but are meaningful for understanding recommendation policies and improving personalization. Different types of feedback models leveraging signals from multiple feedback signals are able to benefit from their complementary advantages. However, feedback mechanisms may also introduce popularity bias and feedback loops, raising fairness concerns for long-tail content and underrepresented user groups. In addition, explicit feedback increases user effort, while implicit feedback often lacks transparency, both of which can negatively affect engagement and trust. To address these challenges, strategies such as explainable recommendation interfaces, interactive feedback designs, and fairness-aware modeling help optimize system performance while maintaining user satisfaction and trust. Future recommender systems should be a balance between prediction accuracy and mitigation of bias, enhancement of fairness, maximization of long-term user value, and interpretability of multi-feedback integration. Related approaches include causal inference, reinforcement learning, large models for contextual information, and deliberate implicit feedback.

## References

[1] Xian, J. (2021). Research on online recommendation methods based on multi-behavior implicit feedback [M]. Donghua University.
[2] Zhang, X., Zhu, N., & Guo, Y. (2024). A survey of session-based recommendation methods based on graph neural networks. Data Analysis and Knowledge Discovery, 8(02), 1-16.
[3] Liu, Z., et al. (2021). Research on trustworthy evaluation of news recommendation algorithms. Journal of Cyber Security, 6(05), 156-168.
[4] Zhang, H., et al. (2022). A survey of privacy-preserving federated recommendation algorithms. Acta Automatica Sinica, 48(09), 2142-2163.
[5] Hu, Y., Koren, Y., & Volinsky, C. (2008). Collaborative filtering for implicit feedback datasets. In 2008 Eighth IEEE international conference on data mining, 263-272.
[6] Wang, H., Zhang, F., Xie, X., & Guo, M. (2018). DKN: Deep knowledge-aware network for news recommendation. In Proceedings of the 2018 world wide web conference, 1835-1844.
[7] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. ACM computing surveys (CSUR), 52(1), 1-38.
[8] Hua, Y., et al. (2020). Research progress on interpretability of deep learning models. Journal of Cyber Security, 5(03), 1-12.
[9] Liu, H., et al. (2022). Neural matrix factorization recommendation for user preference prediction based on explicit and implicit feedback. Computational Intelligence and Neuroscience, 2022(1), 9593957.
[10] Zeng, Z., Dai, H., Zhang, D. J., Zhang, H., Zhang, R., Xu, Z., & Shen, Z. J. M. (2023). The impact of social nudges on user-generated content for social network platforms. Management Science, 69(9), 5189-5208.
[11] Wang, B., McKeown, K., & Ying, R. (2025). DYSTIL: Dynamic Strategy Induction with Large Language Models for Reinforcement Learning. arXiv preprint arXiv: 2505.03209.