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User-Centered Experimental Evaluation of Recommendation Strategies in Online Education

Alma Sheko[1], Shaniko Aliaj[1]

[1] University " Ismail Qemali " Vlorë, Albania

Corresponding author: alma. sheko@univlora.edu.al

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Abstract

Users of online education platforms often struggle to select courses that align with their needs and interests. This challenge arises because there are a large number of online courses. Recommendation systems can help address this challenge by directing users toward courses that are more relevant to their preferences. This paper presents a pilot experimental evaluation of recommendation strategies in online educational systems to assess their impact on user decision-making. A web-based platform was developed as an experimental framework to compare the effects of different recommendation strategies on user behavior. Three recommendation strategies were implemented in this platform: a standard interface without recommendations, a popularity-based recommendation strategy, and a content-based personalization strategy. This experimental platform was distributed to 51 Computer Science students at the University of Vlora in January 2026. During the periment, the system recorded student interactions and course selections. The collected data was then evaluated using several behavioral metrics: the average number of selections per user, the total number of selected courses, the selection rate, and diversity.

To compare the three experimental groups, Repeated-Measures ANOVA was used as a statistical test.

The results show that the standard system reflects a high level of exploration, but with lower efficiency. The popularity-based method reduces the number of choices and was linked to increased user focus. While the content-based approach appears to be more effective, it achieves the highest selection rate and a better balance between exploration and orientation. The Repeated-measures ANOVA showed that recom-

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mendation strategies produce statistically significant differences in users' behavior during course selection. Bonferroni post-hoc comparisons showed significant differences between the standard method and both recommendation methods (popularity-based and content-based). In contrast, no statistically significant difference was found between the content-based and popularity-based approaches.
The study contributes to the literature by providing a user-centered experimental perspective on recommender systems in online education. It shows how different recommendation strategies influence user interaction and decision-making beyond traditional measures of algorithmic performance.

Keywords: *user behavior, recommender systems, online education, course recommendation, ANOVA*

Introduction

The widespread use of online platforms in education offers students a wide range of learning resources. As these resources grow over time, students need to identify the courses that best suit them amid today's information overload. In 1997, Resnick and Varian first introduced recommender systems to help users navigate large information spaces by providing them personalized suggestions based on their preferences and behavior. Over time, recommendation systems have improved, and with the development of artificial intelligence, they have become even more advanced. Nowadays, recommendation systems are very important on modern digital platforms because they help users find content that best suits their interaction history. Recommendation systems are widely used across many fields, such as e-commerce, online education, media, web search, social networks, online advertising, entertainment, and employment platforms (Ricci et al., 2022; Rodriguez et al., 2023; Ko et al., 2022).
Recommendation strategies are categorized into collaborative filtering, content-based filtering, and hybrid methods. In collaborative filtering, the system recommends items based on similarities among users or their history. Whereas, content-based filtering focuses on recommending items that share characteristics with those the user previously preferred, i.e., based on their history. Also, hybrid methods are very important. These methods combine multiple approaches to improve recommendation accuracy and overcome the limitations of the first two categories (Adomavicius and Tuzhilin, 2005; Chaudhari et al., 2024).
In order to improve the personalization and quality of recommendation systems, machine learning and artificial intelligence techniques are being integrated. For example, the use of deep learning has demonstrated the ability to model complex relationships between students and courses, leading to more accurate recommendation systems (Zhang et al., 2019; Chen et al., 2021; Anvitha et al., 2025). In online education platforms, recommender systems are used to support personalized learning and to help students discover appropriate educational resources (Drachsler et al., 2015). According to Blythe (2001), the design of online courses should be done not only according to technical or administrative logic, but should be built in collaboration with students, making them part of the learning and design process. To understand student behavior, we first conduct a pilot study in this project. Kundu et al. (2020), in their study, emphasize that recommendation systems in e-learning are important because they suggest appropriate courses, help students find relevant materials, personalize the learning experience, and increase efficiency and motivation. The future education will be personalized, intelligent, and data-driven, but it must be developed with ethical and pedagogical care (Bekarystankyzy et al., 2026).
Different approaches have been seen in the literature, such as content-based filtering, collaborative filtering, hybrid methods, or machine learning methods, which aim to improve the personalization and accuracy of recommendations in online education (Ma, 2025; Lynn and Emanuel,

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2021; Yin et al., 2020; Amer and Jamal, 2016; Tatineni, 2020). Most of these papers study the optimization of recommendation approaches based on user data or algorithm performance. Meanwhile, a smaller number of studies have addressed the aspect of user behavior when interacting with online learning recommendation systems. However, they often remain limited to descriptive analyses and do not provide direct comparisons between different recommendation strategies in a controlled experimental setting. According to Maphosa et al. (2020), from 2010 to 2019, very few articles were published on course recommendation systems in online learning: only 24 out of 16,000 research papers. Indeed, there is a gap in the literature regarding the impact of different course recommendation strategies in education on user behavior.

Our work aims to address this gap by providing a user-oriented experimental evaluation that compares three different recommendation approaches on an e-learning platform. This study is a pilot experimental evaluation of recommendation strategies in online educational systems. An experimental framework platform was used, called CourseChooser, which is designed to evaluate how three recommendation strategies affect user behavior when selecting online courses. The collected data was then evaluated using multiple evaluation metrics: the average number of selections per user, the total number of selected courses, the selection rate, and diversity. To compare the three experimental groups, we have used Repeated-measures ANOVA, which compares the same user across several conditions to determine whether the conditions produce different results. Bonferroni post-hoc comparisons were used to show differences between pairs of recommendation methods. Groups compared are: Standard vs. Popularity, Standard vs. Content, and Popularity vs. Content.

Given the challenges identified in the wide range of information in online education environments, this study addresses three research questions:

Research Question 1: Does the use of recommendation systems affect user interaction on online course selection platforms?

Research Question 2: Are there statistically significant differences between the methods?

Research Question 3: Which recommendation strategies produce significantly different user selection patterns regarding exploration, focus, and diversity?

This paper is organized into several sections. First, the research methodology is presented, then comes the experimental part of the study, the results, and finally the relevant discussions and conclusions.

Research Methodology

This study aims to design a user-centered experiment to evaluate how different recommendation strategies influence user behavior when selecting courses in an online learning environment. A within-subject repeated-measures design was adopted, in which the same participants interacted with all experimental conditions. The research methodology is based on three main phases: the development of the web platform that serves as an experimental framework, the experimental evaluation, and then the data analysis. This methodology is based on the literature, common research practices in recommender system evaluation combine system implementation, controlled experiments, and data-driven analysis to evaluate the effectiveness of recommendation algorithms (Ricci et al., 2022; Li and Ye, 2020).

Firstly, a web-based platform was developed to simulate an online course environment. This platform was called CourseChooser. The platform's user interface was developed using standard web development technologies (HTML, CSS, and JavaScript). Figure 1 visually presents the system architecture of the CourseChooser platform. The architecture consists of the User Interface, the environment in which students view and select courses. The interface is designed to be simple and intuitive, to minimize usability barriers during the experiment. The data received

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from the user interface is passed to the recommendation engine, which generates course suggestions. Three recommendation strategies have been implemented: the standard strategy, the popularity-based strategy, and the content-based strategy. Another part of the architecture is the Database, responsible for storing information for each course. Information such as course titles, descriptions, and tags was used for recommendation calculations. All user interactions are recorded in the Data Collection Module. Then, these data were used for evaluation and analysis.
As mentioned above, the study implemented multiple recommendation strategies on the course selection platform, CourseChooser. Based on the literature, these strategies represent commonly used methods in recommender systems and enable comparison between non-personalized and personalized recommendation methods (Ricci et al., 2022; Hui et al., 2022; Lahiassi et al., 2023).

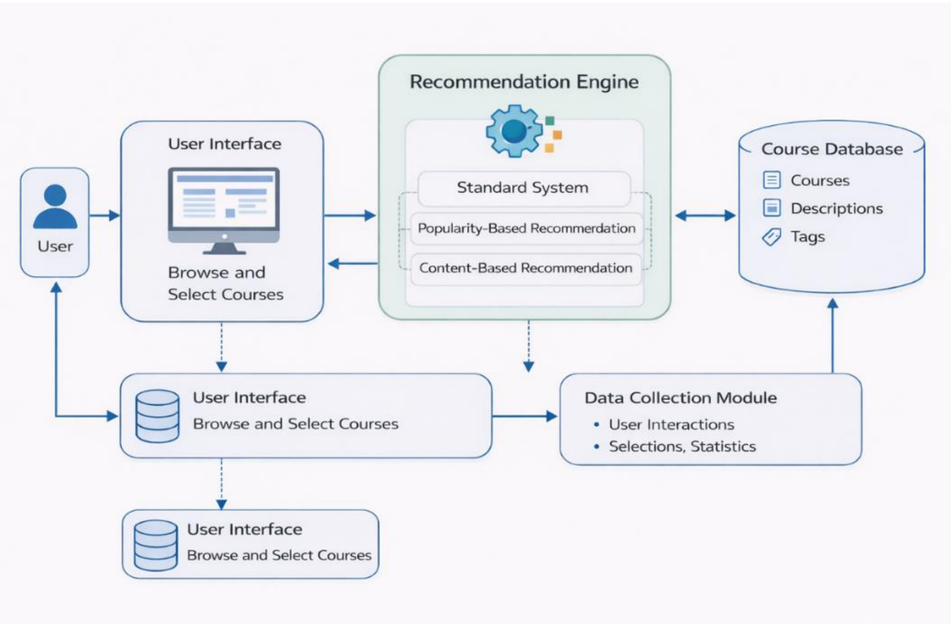
Below is a brief description of each recommendation system.

a. Standard Recommendation System
In the standard selection system, all courses are listed without any recommendation logic. Users are free to explore and choose based on their individual interests.

b.Popularity-Based Recommendation System
The popularity-based recommendation strategy suggests courses based on the frequency of their selection by all users. Courses that are selected more frequently by users yield higher recommendation scores. This strategy assumes that the most popular courses are more likely to be relevant to other users. Due to their ease of implementation and immediate results, popularity-based methods are commonly used in online platforms (Chen et al., 2021; Islam et al., 2022; Elahi et al., 2021). Recommendation points are calculated using the following formula:

$$Scores(course) = selection\ numbers \qquad (1)$$

Figure 1. CourseChooser Architecture System



a.Content-Based Recommendation System

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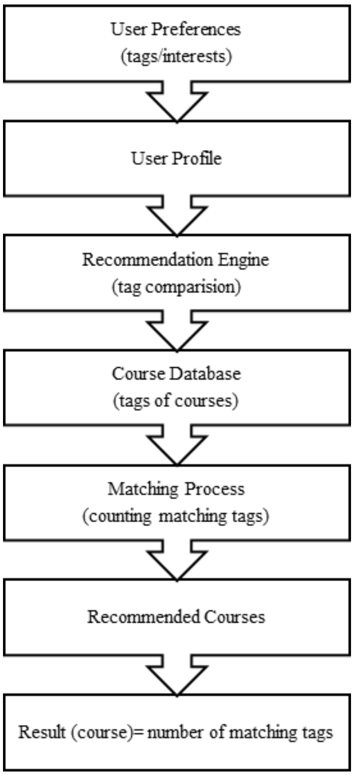
The content-based recommendation strategy evaluates how well the course characteristics match the user's interests. Each course is accompanied by descriptive tags representing topics or fields (for example, AI, Web, Data Science, programming). The recommendation process with this strategy is shown in Figure 2. When a user interacts with the system, the recommendation engine compares these tags with the user's preferences and assigns a score based on the number of matching labels. The recommendation score is calculated using the following formula (Li and Sun, 2025):

Scores(course) = number of matching tags (2)

Content-based filtering is widely used in recommender systems because it allows systems to personalize recommendations according to individual user preferences and item characteristics (Adomavicius and Tuzhilin, 2005; Son and Kim, 2017; Ricci et al., 2022).

Figure 2. Content-based Recommendation Process



Unlike traditional approaches that focus primarily on algorithmic accuracy, this study emphasizes interaction-based metrics that capture how users engage with the system. To assess the impact of different recommendation strategies on user behavior, a set of user-centered evaluation metrics was used. Such metrics are widely used in recommender systems research to evaluate user experience and behavior patterns (Ricci et al., 2021).

The first used metric is the average number of selected courses, which represents the average number of items selected by each user. This metric indicates the level of user exploration, with

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higher values indicating broader interaction, while lower values suggest more focused decision-making. The other metric is selection rate, is defined as the ratio between the number of selected items and the total number of items presented to users. This metric reflects the efficiency and relevance of the recommendation process. Higher values indicate that users are more likely to select items from the recommendations provided. While the diversity metric was used to assess the variety of user choices. Diversity is measured as the number of distinct categories among selected courses. Diversity is commonly used in recommender system evaluation to capture the extent to which recommendations span different topics or domains (Shani and Gunawardana, 2010). Higher diversity values indicate a broader range of interests, while lower values suggest more specialized preferences.

To determine whether the observed differences between recommendation strategies are statistically significant, a Repeated-Measures ANOVA was applied. Repeated-Measures ANOVA is a widely used statistical method when the same participants are tested under multiple conditions, allowing comparison of group means while accounting for within-subject dependence (Field, 2024). Assumptions for repeated-measures ANOVA were checked and found acceptable. Bonferroni-adjusted post-hoc comparisons were also performed to identify pairwise differences. Effect size measures were reported to assess the practical magnitude of the observed effects (Field, 2024). The inferential statistical analysis is based on the number of courses selected, while the metrics of selection rates and diversity are presented in a descriptive manner to interpret user interaction patterns.

Experimental study

The web-based platform was used as a testing environment for comparing methods. It shows course lists and recorded users' choices. The platform included a list of courses from various fields. The courses were categorized into topics such as AI / Data Science, Programming, Networks, Mathematics, etc. The same 51 students interacted with the course selection platform using all three recommendation approaches, administered sequentially in order: standard, popularity-based recommendation, and content-based recommendation. Users were asked to choose the courses they considered most relevant or interesting in each session. The system automatically recorded user interactions through the data collection module. These selections generated datasets containing information about the selected courses, user behavior, and recommendation performance. Experimental evaluation using user interaction data is a widely used method in recommender system research, as it provides insights into how users respond to different recommendation strategies in real-world scenarios (Zhang et al., 2019; Chen et al., 2021; Kundu et al., 2020).

The data obtained from the students included information about course selection, their behavior, and system interactions recorded during the experiment. Microsoft Excel and Jamovi (The Jamovi project, 2024) were used to process and analyze the collected data. We first organized, cleaned, and structured the three sets of experimental data. Then, we calculated the evaluation metrics and summarized them in tables and graphs. This analysis enabled the comparison of three recommendation strategies implemented in the CourseChooser platform. Figure 3 shows the flow of the experimental evaluation.

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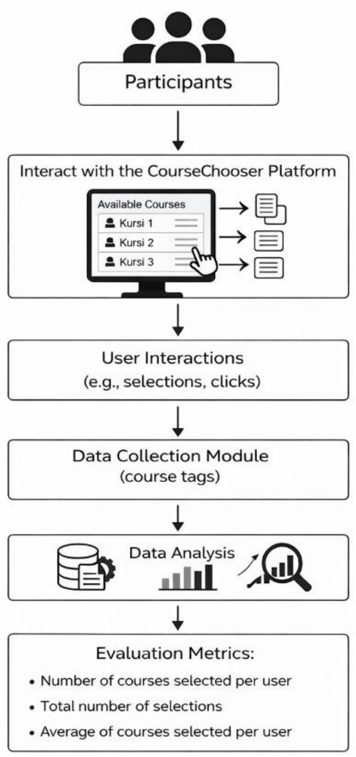
Figure 3. Experimental flow of the CourseChooser Platform



Results

The results provide insights into how different recommendation strategies influenced student interaction and course selection behavior on the online course platform. In this pilot study, 51 users participated. In the first case, no recommendation was applied, and all courses were displayed uniformly in the platform interface. Users selected 176 courses in total, averaging 3.45 courses per user. This high average indicates that when users browse courses without algorithmic recommendations, they tend to explore more options before making decisions. In the second case, the popularity-based recommendation system was implemented, and a total of 115 courses were selected, averaging 2.25 courses per user. The lower average indicates that popularity-based recommendations can more easily guide users toward more frequently selected courses. In the case of a content-based recommendation system, users selected a total of 117 courses, averaging 2.29 per user. Although this average is slightly higher than the popularity-based approach, it remains significantly lower than the standard system, suggesting that personalized recommendations can influence users in the course selection process. In conclusion, the results show that recommendation strategies that combine popularity and content guide users toward more focused selections.

The content-based recommendation strategy was associated with the highest selection rate. Meanwhile, the diversity of course choices is almost the same for all three approaches, meaning that diversity is not greatly affected by method.

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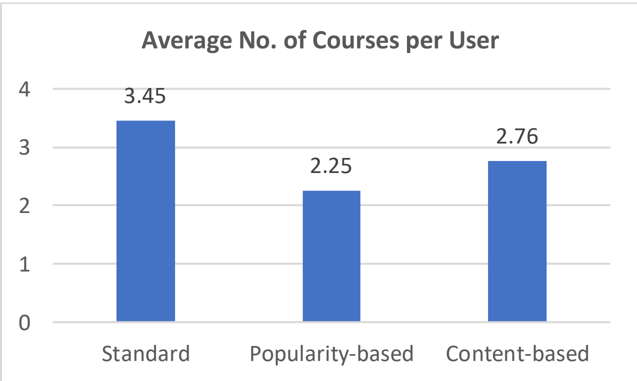
The results of descriptive statistics, including 95% confidence intervals, are presented in **Table 1**.

Figure 4 shows a graph comparing the average number of courses selected through the three recommendation strategies implemented in the experimental *CourseChooser* platform

Table 1. Comparison of Recommendation Strategies

Recommendation Strategies	Number of Users	Total Selections	Average No. of Courses per User	95% CI	Selection Rate (%)	Diversity
Standard	51	176	3.45	[2.88, 4.02]	7%	2.24
Popularity	51	115	2.25	[2.00, 2.47]	12%	2.24
Content	51	117	2.29	[2.06, 2.53]	16%	2.21

Figure 4. Comparison of Recommendation Strategies Based on Average Number of Courses Selected per User



A repeated-measures ANOVA revealed a significant effect of recommendation strategy on the number of selected courses, $F\ (2,102) = 17.30$, $p < .001$, $\eta^2 p = 0.253$ (Table 2). The analysis confirms that the recommendation strategy has a significant and practically important effect on the number of courses users select.

Table 3 shows the results of pairwise comparisons: Standard versus Popularity, Standard versus Content, and Popularity versus Content.

Bonferroni post-hoc comparisons showed significant differences between the standard method and both recommendation methods (popularity-based and content-based) ($p < .001$). No statistically significant difference was found between the content-based and popularity-based conditions ($p = 1.000$) (Lenth, 2023).

Table 2. Results of Repeated-Measures ANOVA analysis.

Effect	df	F	p-value	Partial η^2
Recommendation Strategy	(2, 102)	17.30	< .001	0.253

Table 3. Bonferroni Post-Hoc Comparisons.

Comparison	Mean Difference	p-value
Standard vs Popularity	1.2157	< .001
Standard vs Content	1.1569	< .001
Popularity vs Content	-0.0588	1.000

Discussion

According to experimental findings, it is shown that recommendation systems may affect not only what users choose, but also how they make decisions, how many options they choose, and the extent to which they explore available courses. This highlights the practical importance of recommendation design for improving user experience in e-learning environments, where effective guidance and personalization can support more efficient and satisfying course selection. These findings answer the first research question of whether recommender systems affect user interaction. In the standard system, users explored a larger number of courses on average because they received no guidance from recommendation algorithms. They simply do a manual browsing and exploration to discover available courses. This behavior is consistent with the study by Ricci et al. 2022, which suggests that users tend to explore more extensively when recommendation support is not available.

The second research question is answered by repeated-measures ANOVA analysis, which confirmed statistically significant differences among the three evaluated conditions, suggesting that the design of recommendation mechanisms plays an important role in shaping user interaction patterns. Bonferroni post-hoc comparisons showed that the standard approach differed significantly from the popularity-based and content-based approaches. While no statistically significant differences were found between popularity-based and content-based recommendation approaches. These changes are more noticeable at the level of exploration and focus of choices, while diversity remained relatively stable across the three strategies. Diversity remained relatively stable means that recommendation strategies influenced how users chose courses more than the overall range of their interests. Thus, students tended to choose courses from similar subject areas regardless of the recommendation method applied. All findings of this study align with other researchers who show that recommender systems can support more efficient content discovery and reduce the cognitive effort required when users search for relevant information (Adomavicius and Tuzhilin, 2005; Zhang et al., 2019). In the field of education, personalized recommendation systems have also been shown to help students identify appropriate courses and navigate very large databases (Drachsler et al., 2015; Kundu et al., 2020).

Conclusion

This pilot study analyzes the impact of recommendation strategies on user behavior in an online learning environment. A web-based platform was built as an experimental framework to

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lay the foundations for comparing different recommendation strategies. The platform, called *CourseChooser*, enables students to choose the courses they are interested in from a wide range of courses. Three recommendation strategies were tested and evaluated through *CourseChooser*: the standard recommendation strategy, the popularity-based recommendation strategy, and a content-based recommendation strategy. The same 51 students interacted with the course selection platform using all three recommendation approaches, administered sequentially in order: standard, popularity-based recommendation, and content-based recommendation.

Several user-centric metrics were used for the evaluation: average course selection, selection rate, and diversity. It is concluded that recommendation strategies influenced user behavior. The standard approach led to a higher number of courses selected, reflecting greater exploration but lower efficiency, while the popularity-based approach encouraged more focused choices. The content-based approach achieved the highest selection rate, indicating more relevant and effective recommendations. While diversity remained relatively stable across all three approaches, suggesting that recommendation strategies influenced selection behavior more than the range of user interests. Repeated-measures ANOVA analysis showed that there are statistically significant differences between the three strategies tested. This leads us to conclude that the recommendation strategy really influences user behavior.

The *CourseChooser* platform provides a flexible foundation for evaluating recommendation strategies from a user-centric perspective and for integrating more advanced approaches in future work, including AI-based methods. In this way, the proposed system serves as an experimental framework for analyzing user behavior and supporting the future development of intelligent recommendation strategies in online learning environments.

From a practical point of view, this work shows that implementing recommendation strategies on e-learning platforms appears to improve the user experience. Personalized recommendation strategies can help students reduce information overload and navigate more efficiently.

The findings of this study contribute to the literature by enabling a user-centered experimental perspective on recommender systems in online education. It shows how different recommendation strategies influence user interaction and decision-making beyond traditional measures of algorithmic performance. Our work also has some limitations that will be taken into account for future studies. Since the data was collected as part of a pilot study, the sample size is limited. Also, the participants are relatively homogeneous, which limits the generalizability of the results. We have only tested basic recommendation methods, and the metrics focused primarily on user behavior rather than directly measuring predictive accuracy. Another limitation of this study is that all participants went through the recommendation conditions in the same fixed order (first standard, then popularity-based, and then content-based). As a result, some of the observed differences may partly reflect effects of ordering, familiarization, or learning, and not just the recommendation strategy.

Despite the results obtained from this research, it is intended that in future works we will expand into a broader study, both in techniques and in datasets. Integrating more advanced recommendation algorithms, such as collaborative filtering or hybrid recommendation systems, which combine different recommendation techniques to increase personalization and accuracy (Ricci et al., 2022). Another area to delve deeper into in the future is to add other metrics for evaluation, such as perceived relevance of recommendations, user satisfaction, or long-term user engagement with recommended courses. Meanwhile, increasing the number of users would bring a more powerful statistical analysis. Also, integrating deep learning and machine learning techniques into a recommendation engine can further improve personalization. Deep learning models can capture much more complex relationships between

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users and items, enabling more appropriate and accurate recommendation systems (Zhang et al., 2019; Chen et al., 2021). Future studies should use randomized or counterbalanced experimental designs to reduce potential bias from ranking and improve internal validity.

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