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Research Article

Enhanced Content-Based Filtering Algorithm Applied in Core Topic Recommendation System for First-Year Computer Science Students

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ABSTRACT

This study presented an enhanced content-based filtering algorithm for topic recommendation system tailored for the first-year computer science students at University of the City of Manila. The enhancement focused on addressing the cold-start problem, a common issue experienced by new users caused by the algorithm's dependence on user interactions for generating personalized recommendations. To overcome this, the Felder-Silverman Learning Style Model (FSLSM) was incorporated to create a more comprehensive user profile, enabling consistent personalized recommendations for new users. FSLSM considers four dimensions: (1) Processing Dimension (Active/Reflective), (2) Perception Dimension (Sensing/Intuitive), (3) Input Dimension (Visual/Verbal), and (4) Understanding Dimension (Sequential/Global). Additionally, the user's current semester was included to better align recommendations with their curriculum. The enhanced content-based filtering algorithm demonstrated significant improvements over the baseline, effectively addressing the cold-start problem. It achieved a mean precision of 91.7%, recall of 91.5%, and F1-score of 91.6%, reflecting balanced accuracy and effectiveness. The system also attained a mean average precision (MAP) of 91.7% and an average consistency of 91.7%, ensuring stable and reliable recommendations across users.

Keywords: Cold-start Problem, Content-based Filtering Algorithm, Felder-Silverman Learning Style Model, Personalized Topic Recommendation System.

INTRODUCTION

Content-based filtering (CBF) has become a widely adopted approach in recommender systems due to its ability to deliver personalized recommendations based on the attributes of items and user preferences. Unlike collaborative filtering, which relies on the input and preferences of other users, CBF focuses solely on analyzing content features, enabling it to function effectively even in sparse datasets [1]. This characteristic makes CBF particularly useful in domains such as e-learning, where personalized recommendations can significantly enhance the learning experience by aligning with individual user needs and preferences [2]. Fig. 1 shows the methods used in CBF to perform its tasks. It basically analyses the content of the item lists that are already rated or interacted by the user and then create a user profile.

Profile Learner module is responsible in collecting the data based on the user interaction that will represents the likes and interest. And build a user profile out from it. Then, filtering components works on the user profile through the application of correlation between the user generated user's profile and the list of contents to provide an appropriate recommendation [3], [4], [5].

Despite its advantages, content-based filtering systems are often hindered by the *cold-start problem*, which arises when the system lacks sufficient user interaction data to generate personalized recommendations [6]. This issue is especially prevalent for *new users*, as the absence of historical data limits the system's ability to provide meaningful suggestions. Researchers have proposed various strategies to address this limitation, such as enriching user profiles with external knowledge sources [7] or leveraging content enrichment techniques like TF-IDF for similarity calculations [8]. However, the problem persists, particularly in educational settings where students often lack sufficient interaction history within recommendation platforms [9].

In summary, this research aims to enhance content-based filtering algorithms by addressing the cold-start problem through the integration of FSLSM. By combining user learning preferences with detailed content analysis, the proposed system seeks to provide personalized and relevant recommendations that improve the learning experience for students in academic settings.

METHODS AND METHODOLOGY

Felder-Silverman Learning Style Model

To mitigate the cold-start problem, this study incorporates the *Felder-Silverman Learning Style Model (FSLSM)*, which offers a structured framework for understanding individual learning preferences. FSLSM identifies dimensions such as active vs. reflective and visual vs. verbal learning styles, enabling the creation of comprehensive user profiles that can enhance recommendation accuracy [10]. By leveraging FSLSM, the system can recommend educational content tailored to the unique learning styles of first-year Computer Science students, even in the absence of prior interaction data. This approach not only addresses the cold-start problem but also aligns with the growing emphasis on personalized and adaptive learning environments in e-learning systems [11].

There are different learning style models such as Kolb (1984), Honey and Mumford (1982), and Felder and Silverman (1988), each proposes respective descriptions and classifications for learning styles. But Felder and Silverman who introduces the Felder-Silverman Learning Style Model (or the FSLSM) describe the learning style of every learner in a more detail, distinguishing between preferences on four dimensions [12].

Table 1 illustrates the four dimensions defined by Felder and Silverman in their learning style model: Processing, Perception, Input, and Understanding. Each dimension encompasses two specific learning styles: Active/Reflective for the Processing dimension, Sensing/Intuitive for the Perception dimension, Visual/Verbal for the Input dimension, and Sequential/Global for the Understanding dimension. These dimensions offer a framework for categorizing and analyzing individual learning preferences.

Table 1: Understanding FSLSM dimensions, styles, semantic groups, and strategy

	Style	**Semantic Groups**	**Strategy**
Processing Dimension	Active	try something out social oriented	retain and understand information by doing something (e.g. discussing, explaning)
	Reflective	think about material impersonal oriented	think and understand information quietly
Perception Dimension	Sensing	existing ways concerete materials careful with details	like learning facts
	Intuitive	new ways abstract material not careful with details	often prefer discovering possibilities and relationships
Input Dime nsion	Visual	pictures	remember most of what they see (e.g. pictures, diagrams, etc.)

	Style	Semantic Groups	Strategy
	Verbal	spoken words written words difficulty with visual style	get more out of words (i.e. written and spoken explanations)
Understanding Dimension	Sequential	detail oriented sequential progress from part to the whole	gain understanding in linear steps
	Global	overall picture non-sequential progress relations/connections	learn in large jumps

Additionally, semantic groups within each style are identified is shown in Table 1, providing deeper insights into the characteristics associated with each learning style. These semantic groups facilitate a more nuanced understanding of how students engage with and process information. The identified groups and styles have been validated using Pearson's correlation and empirical frequency analysis, ensuring their reliability and applicability [13].

Furthermore, Felder and Soloman outlined specific strategies tailored to each learning style. These strategies serve as guidelines for aligning educational content and teaching methods with the preferred learning styles of students. This alignment not only enhances the effectiveness of personalized learning but also plays a critical role in building comprehensive user profiles for systems like the one developed in this study [12].

System Design

We have two systems here. First is the existing architecture of Content-Based Filtering Algorithm which is shown in Figure 1. That demonstrates the existing algorithm of a CBF, and it flows.

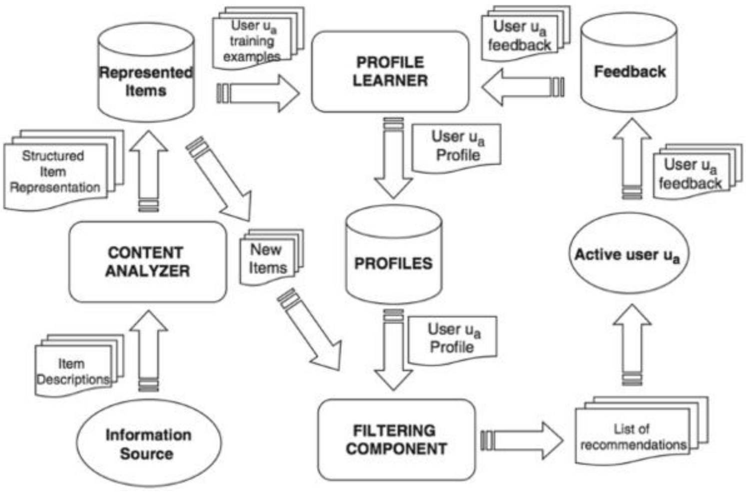

Figure 1. Existing Architecture of Content-Based Filtering Recommendation System

While below is Figure 2, which demonstrates the enhanced architecture of CBF where additional process was added. Figure 2 illustrates the enhanced architecture of the content-based filtering algorithm (CBF), building upon the existing architecture depicted in Figure 1. The enhancement introduces an additional component: the FSLSM Questions, which are based on the Felder-Silverman Learning Style Model. This new component is specifically designed to address the cold-start problem by allowing the system to evaluate and understand new users without relying on prior interactions or historical data.

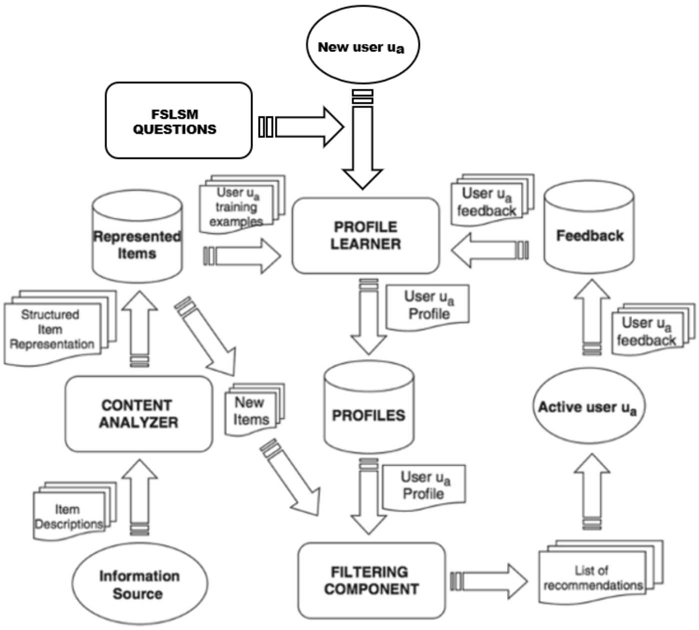

Figure 2. Enhanced Architecture of Content-based Filterling Algorithm – Applying FSLSM

The FSLSM Questions serve as an initial profiling tool, gathering information about the user's learning style across four key dimensions: processing, perception, input, and understanding. By incorporating this step, the system can construct a comprehensive user profile immediately upon the user's entry.

Table 2: Questions for each FSLSM Dimensions

Dimensions	Style	Question
Processing Dimension	Active/Reflective	*Do you like to learn step-by-step and build your understanding gradually, or do you prefer to get an overall view first before diving into details?*
Perception Dimension	Sensing/Intuitive	*When learning a new topic, do you prefer real-world examples and hands-on activities, or do you enjoy exploring new theories and concepts?*
Input Dimension	Visual/Visual	*Do you understand information better through diagrams and images, or through verbal explanations and reading text?*
Understanding Dimension	Sequential/Global	*Do you prefer to discuss new ideas with others as you learn, or do you prefer to reflect on them quietly first?*

The FSLSM questions are shown in Table 2 which compliments the four-dimensions of learning style model in Table 1. This profiling enables the generation of personalized recommendations tailored to the user's unique preferences and learning characteristics, even if the user has no prior engagement with the system. The addition of the FSLSM Questions ensures a smoother onboarding experience for new users while improving the accuracy and relevance of initial recommendations.

Dataset and Testing

The dataset for this study focuses on resources relevant to first-year Computer Science students at University of the City of Manila (a.k.a. Pamantasan ng Lungsod ng Maynila) or also known as University in Manila. It includes syllabi for courses taken during the 1st and 2nd semesters, beginner-level programming topics in languages such as C, C++, and Python, and supplementary materials sourced from W3Schools. These resources were carefully selected to align with the students' curriculum, providing a comprehensive foundation for developing a content-based recommendation system tailored to their academic needs. Table 3 presents the testing setup to evaluate the output of the existing and enhanced algorithms. The test involves comparing the behavior of both algorithms when new users with no prior interactions access the system and the new user who has evaluated first before accessing the system.

Table 3: Test Cases for Existing Content-Based Filtering Algorithm

User	EXISTING CBF ALGORITHM			ENHANCED CBF ALGORITHM			
	Output	**Total Recommendations**	**No. of Relevant Topics**	**Semester**	**Identified Learning Style (FSLSM)**	**Total Recommendations**	**No. of Relevant Topics**
User 1	No Sufficient data to generate recommendations	0	0	First	Sensing, Visual, Active, Sequential	45	44
User 2	No Sufficient data to generate recommendations	0	0	First	Sensing, Verbal, Active, Global	37	34
User 3	No Sufficient data to generate recommendations	0	0	First	Intuitive, Verbal, Reflective, Global	36	34
User 4	No Sufficient data to generate recommendations	0	0	First	Sensing, Visual, Reflective, Global	36	33
User 5	No Sufficient data to generate recommendations	0	0	First	Sensing, Verbal, Reflective, Sequential	36	30
User 6	No Sufficient data to generate recommendations	0	0	Second	Sensing, Visual, Active, Sequential	36	33
User 7	No Sufficient data to generate recommendations	0	0	Second	Intuitive, Verbal, Reflective, Global	36	36
User 8	No Sufficient data to generate recommendations	0	0	Second	Sensing, Visual, Reflective, Global	36	35
User 9	No Sufficient data to generate recommendations	0	0	Second	Sensing, Visual, Reflective, Sequential	36	29
User 10	No Sufficient data to generate recommendations	0	0	Second	Intuitive, Verbal, Reflective, Sequential	36	32

And to determine if the enhanced algorithm consistently performs better than the existing algorithm, various computations are used:

(i) Precision

Precision is the proportion of relevant recommendations to the total recommendations provided by the system. It evaluates the accuracy of the system by measuring how well it recommends relevant topics, ensuring users receive meaningful and useful suggestions. Formula is shown in (1), where P is the Precision, R_r is the Number of Relevant Recommendations, and R_t the Total Recommendations.

$$P = R_r / R_t \qquad \text{Equation (1)}$$

(ii) Recall

This measures how many of the relevant recommendations are correctly provided to the user. It focuses on how well the system retrieves all relevant items for the user to ensure that the system does not miss important recommendations. Formula is shown in (2), where R is the Recall, R_r is the Number of Relevant Recommendations, and T_r is the Total Relevant Topics Available.

$$R = \frac{R_r}{T_r} \qquad \text{Equation (2)}$$

(iii) F1-Score

It is the combination of precision and recall into a single metric to evaluate the balance between them. This provides a single value to measure overall effectiveness. Formula is shown in (3), where F_1 is the F1-Score, P for the Precision, and R for Recall.

$$F_1 = 2 \cdot \frac{P \cdot R}{P + R} \qquad \text{Equation (3)}$$

(iv) Average Consistency

Average consistency measures how reliably a system performs across multiple users or scenarios, ensuring stable and predictable outputs to evaluate systems' stability. Formula is shown in (4), where AC is the Average Consistency, i is Every User, n_{ri} is the Number of Relevant Recommendations for every user, n_{ti} is the Total Recommendations for every user, and N is the Total Number of Users.

$$AC = \frac{\sum_{i=1}^{N} \frac{n_{ri}}{n_{ti}}}{\mathrm{N}} \qquad \text{Equation (4)}$$

(v) Mean Average Precision

This calculates the mean precision scores for all relevant recommendations across multiple users. Formula is shown in (5), where MAP is the Mean Average Precision, i is Every User, N is the Number of Users, R_i is the Total Number of Relevant Topics for Every User, and $Precision@k$ is the Precision at Position k.

$$\mathrm{MAP} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{R_i} \sum_{k=1}^{R_i} \mathrm{Precision@k} \qquad \text{Equation (5)}$$

RESULT AND DISCUSSION:

This section presents a comparison between the existing content-based filtering algorithm and the proposed enhanced algorithm based on the results of the testing and computations, to evaluate the resolution of the cold-start problem and analyze the effectiveness of the enhancements made.

Precision Score

Table 4 illustrates the precision scores of the existing and enhanced content-based filtering (CBF) algorithms for ten users. The existing algorithm fails to generate any recommendations, resulting in undefined precision scores and percentages. This demonstrates its inability to address the cold-start problem, as it relies solely on prior user interactions.

Table 4: Precision Score for Existing and Enhanced CBF

User	**Existing Algorithm**				**Enhanced Algorithm**			
	Total Recommendations	**No. of Relevant Topics**	**Precision Score**	**Prercentage (%)**	**Total Recommendations**	**No. of Relevant Topics**	**Precision Score**	**Prercentage (%)**
User 1	0	0	**Undefined**	**Undefined**	45	44	**0.977778**	**97.7777778**
User 2	0	0	**Undefined**	**Undefined**	37	34	**0.918919**	**91.8918919**
User 3	0	0	**Undefined**	**Undefined**	36	34	**0.944444**	**94.4444444**
User 4	0	0	**Undefined**	**Undefined**	36	33	**0.916667**	**91.6666667**
User 5	0	0	**Undefined**	**Undefined**	36	30	**0.833333**	**83.3333333**

User 6	0	0	**Undefined**	**Undefined**	36	33	**0.916667**	**91.6666667**
User 7	0	0	**Undefined**	**Undefined**	36	36	**1**	**100**
User 8	0	0	**Undefined**	**Undefined**	36	35	**0.972222**	**97.2222222**
User 9	0	0	**Undefined**	**Undefined**	36	29	**0.805556**	**80.5555556**
User 10	0	0	**Undefined**	**Undefined**	36	32	**0.888889**	**88.8888889**

In contrast, the enhanced algorithm provides recommendations for all users, with total recommendations ranging from 36 to 45 and relevant topics ranging from 29 to 44. Precision scores for the enhanced algorithm are consistently high, mostly exceeding 90%, with a few exceptions such as Users 5 (83.33%) and 9 (80.56%). User 7 achieves a perfect precision score of 100%, showcasing the algorithm's accuracy in aligning recommendations with user needs.

Recall Score

Table 5 outlines the recall scores for the existing and enhanced content-based filtering (CBF) algorithms. The existing algorithm shows no recall across all users, as it failed to generate any recommendations or identify relevant topics due to its dependency on prior user interactions. This demonstrates its inability to provide recommendations for new users.

Table 5: Precision Score for Existing and Enhanced CBF

User	Existing Algorithm				Enhanced Algorithm			
	Total Relevant Topics Available	**No. of Relevant Topics**	**Recall Score**	**Prercentage (%)**	**Total Relevant Topics Available**	**No. of Relevant Topics**	**Recall Score**	**Prercentage (%)**
User 1	45	0	**0**	**0**	45	44	**0.97777778**	**97.7777778**
User 2	37	0	**0**	**0**	37	34	**0.91891892**	**91.8918919**
User 3	36	0	**0**	**0**	36	34	**0.94444444**	**94.4444444**
User 4	36	0	**0**	**0**	36	33	**0.91666667**	**91.6666667**
User 5	36	0	**0**	**0**	36	30	**0.83333333**	**83.3333333**
User 6	36	0	**0**	**0**	36	33	**0.91666667**	**91.6666667**
User 7	36	0	**0**	**0**	36	36	**1**	**100**
User 8	36	0	**0**	**0**	36	35	**0.97222222**	**97.2222222**
User 9	36	0	**0**	**0**	36	29	**0.80555556**	**80.5555556**
User 10	36	0	**0**	**0**	36	32	**0.88888889**	**88.8888889**

On the other hand, the enhanced algorithm displays a significant improvement, with recall scores ranging between 80.56% and 100%. For instance, User 7 achieved a perfect recall score of 100%, reflecting the algorithm's ability to recommend all relevant topics available for that user. Other users, such as User 1 (97.78%) and User 3 (94.44%), also demonstrated high recall scores, indicating that the enhanced algorithm identified a substantial majority of relevant topics. However, a few users, such as User 9 (80.56%), showed comparatively lower recall scores, suggesting that while the enhanced system performs well overall, there may still be minor gaps in fully capturing all relevant topics for certain users.

F1-Score

Table 6 presents the F1-scores for the existing and enhanced content-based filtering (CBF) algorithms. The existing algorithm shows no F1-scores across all users, as both precision and recall scores were undefined due to its inability to generate any recommendations or identify relevant topics for new users. This highlights the existing algorithm's ineffectiveness in addressing the cold-start problem.

Table 6: Precision Score for Existing and Enhanced CBF

User	Existing Algorithm				Enhanced Algorithm			
	Precision Score	**Recall Score**	**F1-Score**	**Prercentage (%)**	**Precision Score**	**Recall Score**	**F1-Score**	**Prercentage (%)**
User 1	Undefined	0	**Undefined**	**Undefined**	0.977777778	0.9777778	**0.97777778**	**97.7777778**

User 2	Undefined	0	**Undefined**	**Undefined**	0.918918919	0.9189189	**0.91891892**	**91.8918919**
User 3	Undefined	0	**Undefined**	**Undefined**	0.944444444	0.9444444	**0.94444444**	**94.4444444**
User 4	Undefined	0	**Undefined**	**Undefined**	0.916666667	0.9166667	**0.91666667**	**91.6666667**
User 5	Undefined	0	**Undefined**	**Undefined**	0.833333333	0.8333333	**0.83333333**	**83.3333333**
User 6	Undefined	0	**Undefined**	**Undefined**	0.916666667	0.9166667	**0.91666667**	**91.6666667**
User 7	Undefined	0	**Undefined**	**Undefined**	1	1	**1**	**100**
User 8	Undefined	0	**Undefined**	**Undefined**	0.972222222	0.9722222	**0.97222222**	**97.2222222**
User 9	Undefined	0	**Undefined**	**Undefined**	0.805555556	0.8055556	**0.80555556**	**80.5555556**
User 10	Undefined	0	**Undefined**	**Undefined**	0.888888889	0.8888889	**0.88888889**	**88.8888889**

In contrast, the enhanced algorithm demonstrates consistently high F1-scores for all users, ranging from 80.56% to 100%. For example, User 7 achieved a perfect F1-score of 100%, reflecting the balance between precision and recall in providing accurate and comprehensive recommendations. Other users, such as User 1 (97.78%) and User 3 (94.44%), also exhibited strong F1-scores, indicating the enhanced algorithm's effectiveness in both identifying relevant topics and minimizing irrelevant recommendations. However, some users, such as User 9 (80.56%), displayed relatively lower F1-scores compared to others, suggesting opportunities for further improvement in achieving consistency across all users.

Average Consistency

Table 7 illustrates the average consistency scores for the existing and enhanced content-based filtering (CBF) algorithms. The existing algorithm's consistency scores remain undefined across all users due to its inability to generate any recommendations or identify relevant topics for new users, underscoring its limitations in addressing the cold-start problem.

Table 7: Precision Score for Existing and Enhanced CBF

User	**Existing Algorithm**				**Enhanced Algorithm**			
	Total Recommendations	**No. of Relevant Topics**	**Consistency**	**Prercentage (%)**	**Total Recommendations**	**No. of Relevant Topics**	**Consistency**	**Prercentage (%)**
User 1	0	0	**Undefined**	**Undefined**	45	44	**0.97777778**	**97.7777778**
User 2	0	0	**Undefined**	**Undefined**	37	34	**0.91891892**	**91.8918919**
User 3	0	0	**Undefined**	**Undefined**	36	34	**0.94444444**	**94.4444444**
User 4	0	0	**Undefined**	**Undefined**	36	33	**0.91666667**	**91.6666667**
User 5	0	0	**Undefined**	**Undefined**	36	30	**0.83333333**	**83.3333333**
User 6	0	0	**Undefined**	**Undefined**	36	33	**0.91666667**	**91.6666667**
User 7	0	0	**Undefined**	**Undefined**	36	36	**1**	**100**
User 8	0	0	**Undefined**	**Undefined**	36	35	**0.97222222**	**97.2222222**
User 9	0	0	**Undefined**	**Undefined**	36	29	**0.80555556**	**80.5555556**
User 10	0	0	**Undefined**	**Undefined**	36	32	**0.88888889**	**88.8888889**
Average Consistency			**Undefined**	**Undefined**			**0.91744745**	**91.7447447**

On the other hand, the enhanced algorithm demonstrates consistently high consistency scores across all users, with values ranging from 80.56% to 100%. For instance, User 7 achieved a perfect consistency score of 100%, indicating that all recommendations were relevant to the user's profile. Other users, such as User 1 (97.78%) and User 3 (94.44%), also showed high consistency, reflecting the enhanced algorithm's capability to maintain relevance in its recommendations. However, User 9 displayed a relatively lower consistency score of 80.56%, indicating slight variability in the system's performance across different users.

The average consistency score for the enhanced algorithm was 91.74%, signifying its overall effectiveness in providing relevant recommendations consistently for new users. This result highlights the enhanced algorithm's ability to address the cold-start problem effectively, ensuring personalized and relevant recommendations from the outset.

Mean Average Precision

Table 8 displays the mean average precision scores for both the existing and enhanced content-based filtering (CBF) algorithms. The existing algorithm consistently fails to generate any precision scores for new users, with all values listed as "Undefined." This outcome highlights its inability to provide relevant recommendations, particularly for users with no prior interaction history, further confirming its susceptibility to the cold-start problem.

Table 8: Precision Score for Existing and Enhanced CBF

User	Existing Algorithm		Enhanced Algorithm	
	Precision Score	Precision Average	Precision Score	Precision Average
User 1	**Undefined**	**Undefined**	**0.97777778**	**0.91744745**
User 2	**Undefined**		**0.91891892**	
User 3	**Undefined**		**0.94444444**	
User 4	**Undefined**		**0.91666667**	
User 5	**Undefined**		**0.83333333**	
User 6	**Undefined**		**0.91666667**	
User 7	**Undefined**		**1**	
User 8	**Undefined**		**0.97222222**	
User 9	**Undefined**		**0.80555556**	
User 10	**Undefined**		**0.88888889**	

Conversely, the enhanced algorithm demonstrates significant improvements, with precision scores ranging from 0.8056 (80.56%) to 1 (100%). For example, User 7 achieved a perfect precision score of 1, indicating that all recommended topics were highly relevant. Similarly, other users, such as User 1 (0.9778) and User 3 (0.9444), exhibit consistently high precision, showcasing the enhanced algorithm's ability to deliver accurate and personalized recommendations.

The overall average precision score for the enhanced algorithm is 0.9174 (91.74%), underscoring its effectiveness in generating precise recommendations for users, even in the absence of prior interactions. This result highlights the enhanced algorithm's capability to overcome the limitations of the existing algorithm, particularly in addressing the cold-start problem and ensuring the relevance of its recommendations.

CONCLUSION

In summary, the results demonstrate the effectiveness of the enhanced content-based filtering algorithm in overcoming the cold-start problem and delivering personalized recommendations tailored to first-year computer science students. By incorporating the Felder-Silverman Learning Style Model (FSLSM), the system successfully addressed the limitations of the existing algorithm, enabling accurate initial recommendations even for users without prior interactions. Key metrics, including high precision, recall, F1-scores, and average consistency, validate the robustness and reliability of the enhanced algorithm. These outcomes highlight the algorithm’s ability to provide relevant and diverse learning resources, significantly improving the user experience and supporting students' academic progression. The findings emphasize the practical applicability of integrating learning style models into recommendation systems, paving the way for further advancements in personalized educational technologies.

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DATA AVAILABILITY

No new data were created or analyzed in this study. Data sharing is not applicable to this article

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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