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A Modified Hybrid Content-Aware Course Recommendation Model for Moodle-Based Learning Management System

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Abstract— Existing course recommendation systems in Learning Management Systems (LMS) often restrict suggestions to the same categories as a user's previously taken courses, limiting diverse course discovery. To address this, this research developed a personalized, cross-category course recommendation system for a data-constrained institutional LMS. This research adapted the Hybrid Content-Aware Course Recommendation (HCACR) framework, integrating a metadata-based user-interest model, a K-Modes-based demographic characteristic model, and a sequential course history model to mitigate data sparsity and cold-start problems. The system was deployed in a Moodle-based environment and evaluated by 171 users. Experimental results show that the model achieved a precision of 26.78% and a recall of 31.07%, which are reasonable given the data constraints in internal government education contexts. Crucially, the system obtained an excellent System Usability Scale (SUS) score of 86.25, indicating high user satisfaction despite the moderate algorithmic precision. While the reliance on sparse metadata limits semantic richness compared to full-content models, this study demonstrates that a hybrid approach is a feasible and effective solution for enhancing course discovery in institutional settings with limited data access.

Keywords— Course Recommendation; Educational Technology; Hybrid Recommender System; Moodle LMS; Usability Evaluation.

I. INTRODUCTION

The rapid advancement of technology has profoundly transformed the education sector, giving rise to a wide range of digital learning innovations, including emerging and immersive learning technologies reported in recent studies [1][2]. These developments have accelerated the adoption of e-learning, which encompasses both formal and informal learning supported by electronic media [3]. In practice, e-learning is commonly implemented through a Learning Management System (LMS). An LMS is a web-based application designed to manage learning activities, materials, and participant data, enabling interactive education accessible from anywhere [4][5].

LMS platforms host an ever-expanding catalogue of courses, offering unprecedented access to learning materials [6]. However, this abundance introduces a significant challenge: information overload, which can overwhelm users in selecting suitable courses [7]. Students must identify courses that support immediate academic goals while enhancing long-term career prospects in a competitive market [8]. This challenge can be effectively addressed by integrating a course recommender system within the LMS [6].

In educational contexts, recommendation systems aim not just to predict preferences, but to guide learners toward pedagogical goals by presenting items that align with specific user needs [8]. Within an LMS, it reduces the time and effort required to find relevant courses [7]. By suggesting curated courses that match learner competencies, interests, and characteristics, it simplifies selection and enhances the overall learning journey [8].

Moodle is among the most popular open-source LMS platforms, valued for its ease of installation, user-friendly interface, cost-free nature, and widespread adoption [9][10]. A recent study indicates that the platform has surpassed 250 million registered users and has proven effective in enhancing student performance, attitudes, and satisfaction [11]. Despite this widespread use, existing Moodle course recommendation mechanisms remain limited, as they primarily suggest courses within the same categories users have previously accessed. Such category-based recommendations restrict exploration and fail to support truly personalized learning paths. Consequently, there is a clear need for a more intelligent recommendation approach that can suggest relevant courses across categories by leveraging a deeper understanding of learners' interests and characteristics.

Recommendation systems typically employ three foundational methods: Content-Based Filtering (CBF), Knowledge-Based Filtering (KBF), or Collaborative Filtering (CF) [8][12]. While CBF focuses on item attributes [13] and KBF relies on explicit knowledge bases [14], CF, which groups users with similar preferences [15], remains the most prevalent method in educational contexts [16]. This method is particularly advantageous for Moodle environments as it does not require detailed item descriptions, making it suitable for platforms where course metadata may be sparse [17]. Nevertheless, conventional CF approaches often suffer from performance degradation under cold-start conditions for new users and data sparsity in user–item interactions [14].

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To address the limitations of conventional collaborative filtering in LMS environments, this study designs, develops, and evaluates a personalized course recommender system based on the Hybrid Content-Aware Course Recommendation (HCACR) method proposed by Jing and Tang [18]. While the original HCACR framework constructs user interest models from full-course content and determines weighting parameters via data-driven grid search, this study introduces two key methodological modifications. First, the user interest model is derived from instructor-provided course metadata rather than complete learning content, enabling a more feasible, computationally efficient topic modelling approach on platforms with restricted access to instructional materials. Second, this study explores expert-informed approaches, including the Analytic Hierarchy Process (AHP), as alternatives to exhaustive parameter search for estimating the weighting of the hybrid recommendation components. These methodological adaptations are implemented and evaluated within a real-world institutional Moodle-based LMS, and their effectiveness is assessed in terms of recommendation accuracy and user-perceived usability.

II. Research Methodology

This study employs a quantitative experimental research design to develop and evaluate a personalized course recommendation system. The proposed system adapts the Hybrid Content-Aware Course Recommendation (HCACR) method and is implemented within a Moodle-based LMS at a government training institution in Indonesia. The research workflow consists of data collection and pre-processing, recommendation model construction, and performance and usability evaluation.

A. Data Preparation

The dataset was obtained by performing a full join between the Moodle LMS database and the institutional human resources database. Data were extracted in CSV format and represent system usage up to November 29, 2023. Course-related data consisted of metadata and descriptive text from 110 courses. Text pre-processing was applied to ensure suitability for topic modelling, including tokenization, case normalization, punctuation removal, and stopword removal.

User-related data were collected to support both interaction modelling and user characterization. Interaction information was derived from enrollment and activity records. Users were categorized into active users with complete interaction logs and users whose historical interactions were inferred from course completion records. Users with no recorded activity were excluded. In addition, demographic and professional attributes, such as age, gender, work unit, position, tenure, and education level, were incorporated to support user-characteristic modelling.

B. HCACR Model Construction

The recommendation model extends the HCACR framework by integrating three components: User Interest, User Characteristics, and Course History. The overall architecture of the model is illustrated in Fig.1.

The User Interest Model ($weight_a$) captures user preferences based on previously accessed courses. Course metadata were modelled using Latent Dirichlet Allocation (LDA) to identify latent topics. Based on coherence score analysis, 20 topics were selected as the optimal representation.

For each user u, an interest vector p_u was computed as the average of topic vectors t_d from the user's web page access history logs (L_u) where n_u represents the total number of web pages accessed by the user, as defined by Equation (1). User similarity was calculated using cosine similarity using Equation (2). The user interest weight for a course c was derived from the top-K most similar users, subject to a similarity threshold of 0.5. When fewer than 100 users met this threshold, K was set to 100 to ensure sufficient neighborhood coverage using Equation (3).

$$p_u = \frac{1}{n_u} \sum_{d \in L_u} t_d \quad (1)$$

$$sim(u_i, u_j) = \frac{p_{u_i}^T \cdot p_{u_j}}{\|p_{u_i}\| \times \|p_{u_j}\|} \quad (2)$$

$$weight_a(u, c) = \frac{1}{K} \sum_{u' \in U_{u,K}} sim(u_i, u_j) \text{ x } I_{C_{u'}}(c) \quad (3)$$

The User Characteristic Model ($weight_d$) addresses the cold-start problem by leveraging demographic and professional attributes. Users were clustered using the K-Modes algorithm, which is suitable for categorical data. Users within the same cluster are assumed to share similar learning preferences. The user characteristic weight was calculated as the proportion of users in the same cluster who had previously taken course c using Equation (4).

$$weight_d(u, c) = \frac{1}{|U_{l_u}|} \sum_{u' \in U_{l_u}} I_{C_{u'}}(c) \quad (4)$$

The Course History Model ($weight_p$) captures sequential learning behaviour by modelling course transition patterns. A transfer probability $tp(c_i, c_j)$ was defined as the likelihood that users who completed the course c_i subsequently enrolled in the course c_j using Equation (5). The course history weight for a user u and candidate course c was computed as the sum of transition probabilities from all previously completed courses using Equation (6).

$$tp(c_i, c_j) = \frac{|\{u | u \in U_{c_i} \cap U_{c_j},\ t_{u,i} < t_{u,j}\}|}{|U_{c_i}|} \quad (5)$$

$$weight_p(u, c) = \sum_{c' \in C_u} tp(c', c) \quad (6)$$

The Final Recommendation Score is the weighted linear aggregation of the three model components, as shown in Equation (7).

$$weight(u, c) = \propto \times weight_a(u, c) + \beta \times weight_d(u, c) + \gamma \times weight_p(u, c) \quad (7)$$

This study explored the use of the Analytic Hierarchy Process (AHP) as a potential approach to estimate the

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weighting coefficients (α, β, γ) for the hybrid recommendation components based on expert judgment. The procedure involved constructing a pairwise comparison matrix to assess the relative importance of User Interest, User Characteristics, and Course History, and then verifying consistency using the Consistency Ratio as defined by [19]. Expert judgments produce a consistency ratio exceeding the acceptable threshold of 10 per cent, indicating insufficient consistency. The weighting scheme is therefore replaced with an equal weighting strategy, in which each component contributes one-third to the final score. This approach ensures model robustness while minimizing potential bias arising from inconsistent expert assessments. Finally, a post-processing rule was applied to remove inactive courses superseded by newer versions from the final recommendation list.

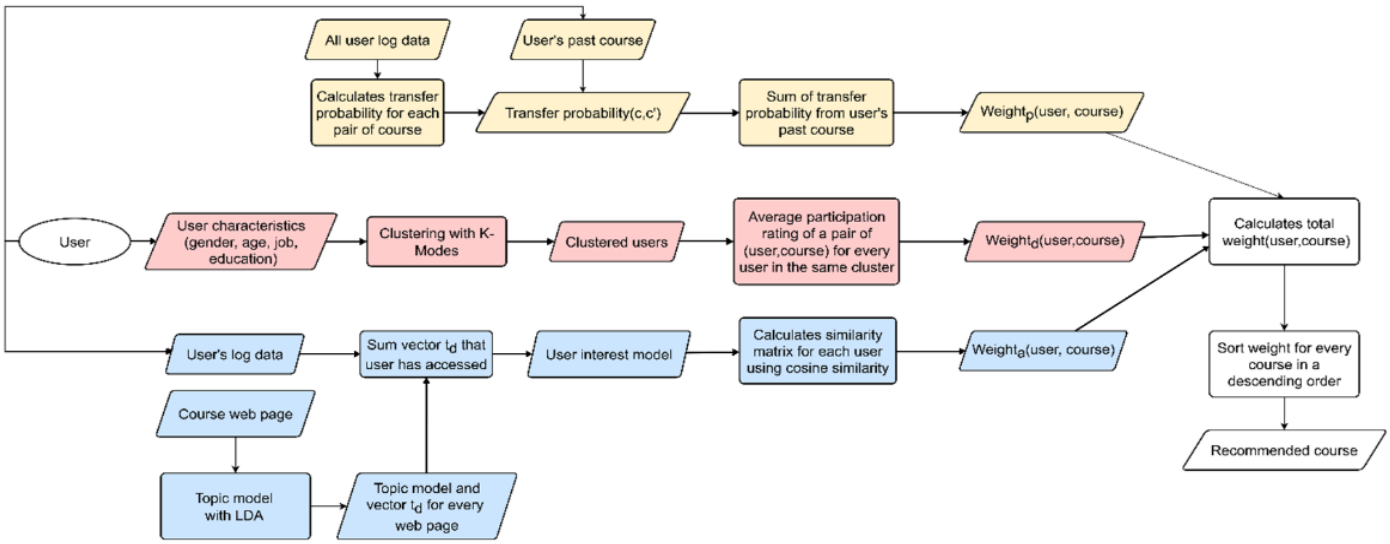

Fig.1. Flow of the Modified HCACR Model

C. *Model Evaluation*

Model performance was evaluated using standard statistical metrics, specifically Precision, Recall, and F1-Score. These metrics provided an objective assessment of the model's accuracy and relevance in generating course recommendations based on the testing dataset.

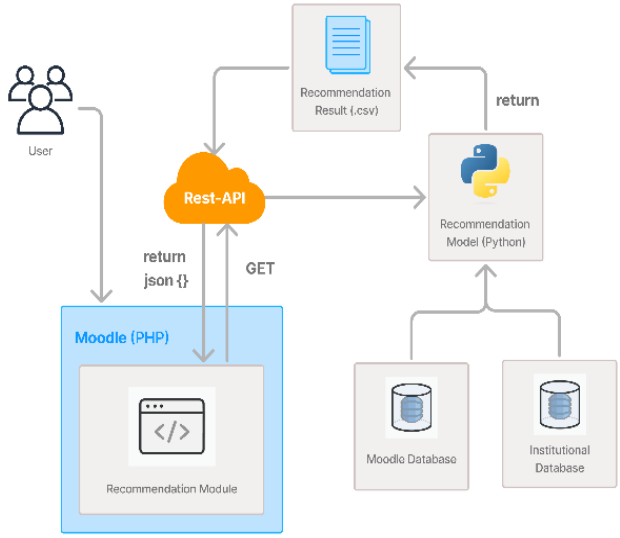

Fig.2. Architecture of the Proposed Integrated Recommendation System

D. *Model Deployment and Usability Testing*

The final model was deployed as an integrated module within the Moodle LMS, interfacing via a REST API that acts as an intermediary between the core recommendation engine and the Moodle front end. The overall system architecture, illustrating how the Moodle platform requests and receives recommendations, is depicted in Fig. 2.

Following the deployment, the system underwent comprehensive testing. Black-box testing was conducted to ensure the system functioned as intended and met functional requirements. Furthermore, system usability was assessed using the System Usability Scale (SUS). A questionnaire was distributed to 3,692 registered LMS users, yielding 171 valid voluntary responses. This survey was conducted to evaluate users' subjective perceptions and the usability of the deployed recommendation module.

III. Result and Discussion

This section presents the empirical findings from the model construction and evaluation phases. The results are presented objectively, covering parameter tuning, model performance metrics, model deployment, and usability result.

A. *Dataset Overview*

After data collection, cleaning, and integration from the Moodle and institutional databases, the final dataset for model

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construction was established. The dataset comprised records from 3,692 active users and their corresponding interactions (e.g., course completions and page views) across all available courses. The course metadata text was then pre-processed using tokenization, lowercase conversion, punctuation removal, and stopword removal. To ensure appropriate handling of Indonesian-language content, tokenization was performed with the NLTK library, stopword removal was conducted with the Sastrawi library, and further refinement was performed using a manually curated stopword corpus to eliminate domain-specific and non-informative terms.

B. Model Parameter Tuning

The model's construction involved two key steps of parameter optimization. First, for the User Interest Model, the optimal number of topics for the Latent Dirichlet Allocation (LDA) model was determined. A coherence score analysis was performed, which indicated that 20 topics yielded the highest score of 0.6317, suggesting the most coherent and interpretable topic structure for the available course data (Fig.3). Second, for the User Characteristic Model, the optimal number of user clusters for the K-Modes algorithm was identified. The silhouette score was calculated for cluster counts ranging from 2 to 10. The analysis showed that 4 clusters achieved the highest silhouette score, indicating the most meaningful grouping of users based on their demographic data (Fig.4).

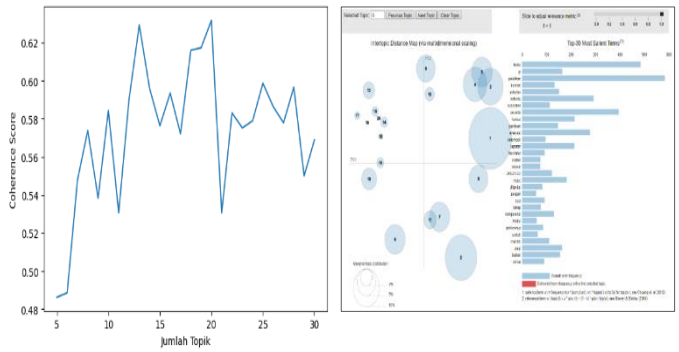

Fig.3. Coherence Score and Topic Model Visualization

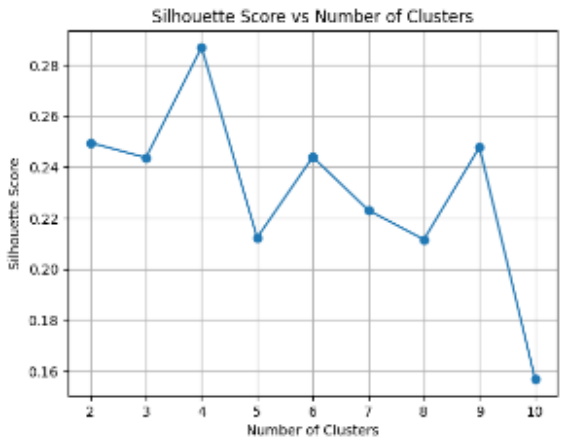

Fig.4. Silhouette Score Plot for k = 2-10

The model tuning, the three individual weight components, such as user interest, user characteristics, and course history, were calculated for each user-course pair. Table I provides examples of these calculated weights, which serve as the intermediate inputs before being combined into a final recommendation score.

TABEL I
EXAMPLES OF INDIVIDUAL WEIGHT COMPONENTS

Type	User Course Pair (*UserID, CourseID*)	Weight
User Interest	(5, 2683)	0.001826
	(5, 2761)	0.000474
User Characteristics	(5, 2677)	0.012886
	(5, 2758)	0.016752
Course History	(30049, 2740)	0,967058
	(50656, 2746)	0,004705

C. Recommendation Model Performance

The effectiveness of the recommendation model was evaluated through a questionnaire distributed to 3,692 active users, yielding 171 valid voluntary responses.

Model performance was assessed using three standard evaluation metrics, calculated as macro averages across all respondents. The results show a precision of 26.78%, a recall of 31.07%, and an F1-score of 28.77%, representing the recommendation model's mean performance. To illustrate the practical outcome of the system. Table II presents the top 10 course recommendations generated for a sample user (ID 35836), ranked by the final combined weight.

TABEL II
EXAMPLES OF TOP 10 RECOMMENDED COURSES FOR ID 35836

Course ID	Course Category	Final Weight
2740	Specific Functional Training	0.069378
2722	Basic Civil Servant Training	0.036248
46	Census/Survey Instructor Training	0.023757
52	Census/Survey Instructor Training	0.021280
2725	Basic Civil Servant Training	0.015665
2719	Basic Civil Servant Training	0.015374
49	Census/Survey Instructor Training	0.010640
2389	Census/Survey Instructor Training	0.007579
2677	Basic Civil Servant Training	0.004373
2671	Specific Functional Training	0.004373

D. Deployment on the LMS

The design and implementation process detailed in the Methodology section resulted in a fully functional recommendation module integrated into the Moodle homepage. As shown in Fig.5, the user interface was designed to align with Moodle's native 'Boost' theme. The final module presents users with a list of ten recommended courses, each displaying key information such as the course name, description, and category. A 'View Course' button is provided for each recommendation, allowing users to navigate directly to the respective course page for more details or to enrol.

Data from the backend recommendation engine is dynamically populated in this interface via a REST API. When a user visits the page, a `GET` request to the `/{User ID}` endpoint returns a JSON response containing a list of recommended course IDs (Fig.6). Upon receiving a successful response, the Moodle module fetches the corresponding course details. It renders the final recommendation list for the user.

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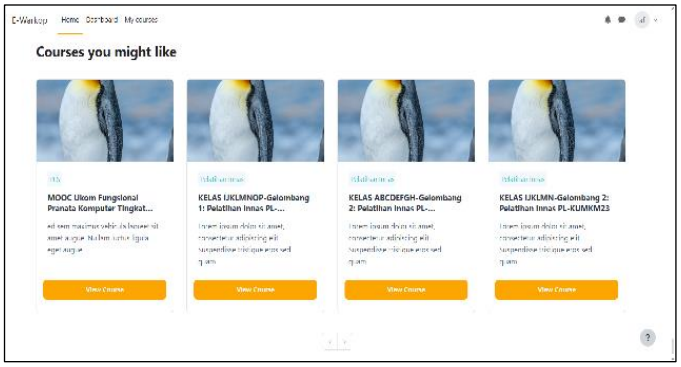

Fig.5. User Interface Implementation

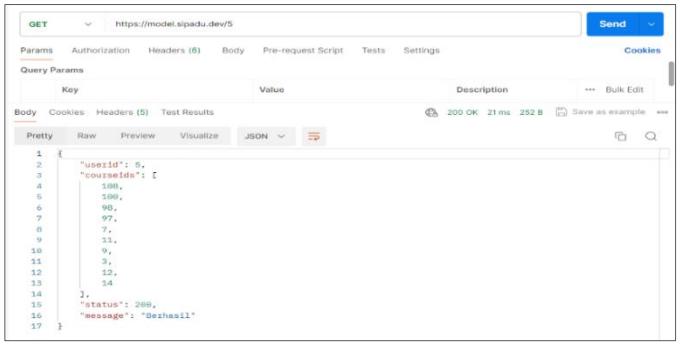

Fig.6. API Responses

E. System Usability

The usability of the deployed recommendation module within the Moodle LMS was assessed using the System Usability Scale (SUS). The evaluation yielded an average SUS score of 86.25. This score is considered "excellent" and falls within the top percentile for system usability, indicating a high level of user acceptance and satisfaction.

F. Discussion

The personalized course recommendation system developed in this study demonstrates meaningful progress from both algorithmic and user-centric perspectives. The proposed model achieved a precision of 26.78%, a recall of 31.07%, and an F1-score of 28.77%. These values may appear moderate in general recommender systems. The research [18], in their foundational HCACR study on the XuetangX MOOC platform, reported a conversion rate of 19.3% in online experiments. The comparable performance observed in this study suggests that the modified HCACR approach remains effective when applied in a more constrained institutional LMS environment rather than a large-scale MOOC setting.

A key contribution of this research is the presentation of a novel case study within a government institutional LMS, addressing the limitations of existing Moodle recommendation plugins that rely primarily on category-based suggestions. Empirical results, as illustrated in Table 2, show that the recommended courses span multiple categories, including functional training, basic civil servant training, and census/survey-related programs. This indicates that the hybrid model successfully breaks category-based filtering barriers by integrating user interests, demographic similarities, and learning history, thereby enabling broader course exploration beyond users' immediate historical patterns.

From a methodological standpoint, the results highlight the implications of adapting HCACR to an institutional context. Unlike the original HCACR model, which uses extensive learning content and a large number of topics, this study relies on instructor-provided course metadata. It identifies 20 optimal topics through coherence analysis. The limited specificity of metadata contributes to overlapping topics and constrains recommendation accuracy. Nevertheless, the hybrid nature of the model compensates for these limitations, as reflected in positive user perceptions and recommendations that are generally relevant.

The discrepancy between moderate accuracy metrics and excellent usability provides an important insight. The System Usability Scale (SUS) score of 86.25, classified as "excellent," indicates that users perceived the recommendations as useful, understandable, and supportive of their learning goals. This suggests that, in organizational LMS environments, perceived usefulness, diversity of recommendations, and ease of interaction may have a greater influence on acceptance than strict predictive accuracy alone. Consequently, usability emerges as a critical success factor for recommender systems in non-commercial learning contexts.

Despite these strengths, several limitations remain. The first is the reliance on metadata-based topic modelling, which limits semantic richness. Second, user clustering based on demographic attributes shows weak separation, as evidenced by silhouette scores near 0. This suggests that demographic attributes alone may not strongly distinguish learner groups within this institution. Third, the relatively low F1-score indicates that the model has not yet fully captured institutional constraints, particularly mandatory job requirements and prerequisite rules that are not explicitly represented in the available metadata. In addition, the current recommendation mechanism operates statically and does not adapt to changes in users' learning activities over time. To address these issues, future research should focus on incorporating richer content sources, exploring alternative clustering methods, and developing dynamic recommendation strategies to improve system performance further.

IV. CONCLUSION

This study successfully addressed the challenge of category-bound recommendations in institutional Learning Management Systems (LMS) by developing and evaluating a personalized course recommendation system based on a modified Hybrid Content-Aware Course Recommendation (HCACR) method. The model was specifically adapted for internal government training environments, where data availability and user roles differ significantly from those on public MOOC platforms.

The research concludes that integrating user-interest modelling derived from sparse course metadata with demographic clustering and course history analysis provides a robust solution for enhancing course discovery. While the

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algorithmic performance, with a precision of 26.78% and a recall of 31.07%, is moderate, it remains reasonable given the data constraints in the educational sector. Crucially, the integrated system passed all functional scenarios during black-box testing while achieving an excellent System Usability Scale (SUS) score of 86.25. This validates that the solution is highly usable and well-accepted by end-users, effectively overcoming the limitations of traditional, siloed recommendation plugins.

However, the study acknowledges several limitations regarding data and methodology. Reliance on instructor-provided metadata rather than full learning content led to overlapping latent topics, limiting the granularity of user interest profiles. Additionally, the demographic clustering yielded low silhouette scores, indicating weak separation between user groups. Furthermore, the use of static weighting coefficients and the inability to incorporate mandatory job-role constraints limited the model's adaptability to specific institutional requirements. Additionally, the evaluation results may reflect a degree of self-selection bias inherent in the voluntary questionnaire process.

Future research should focus on addressing these constraints to refine recommendation accuracy further. Recommendations for improvement include implementing advanced Natural Language Processing (NLP) techniques to extract richer semantic features from course syllabi or materials, thereby reducing topic overlap. Furthermore, developing a dynamic weighting mechanism that adapts to real-time user interactions would enhance the system's responsiveness. Finally, integrating specific institutional rules, such as job-role prerequisites, into the filtering logic would significantly improve the recommendations' relevance and practical utility.

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