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Development of an ALS-Based Collaborative Filtering Model for Authentic Learning Recommendations in Moodle

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Abstract

Personalized learning recommendations in Learning Management Systems (LMS) often rely on learner interaction patterns but may not adequately address competency gaps and authentic skill development. This study proposes ACTS-CF (Authenticity-aware Collaborative Filtering), a recommendation model that integrates Moodle learner interaction data, implicit feedback, Alternating Least Squares (ALS), and Skill Authenticity-based competency gap analysis. Moodle learning activities are transformed into learner–item interactions, and implicit ALS is used to generate candidate recommendations. These recommendations are then refined using learners' Skill Authenticity deficiencies to prioritize learning activities that support authentic skill development. The model was evaluated against baseline ALS using Precision@5, Recall@5, and Normalized Discounted Cumulative Gain (NDCG@5). ACTS-CF achieved the same Precision@5 (0.4667) and Recall@5 (0.3525) as ALS, while improving NDCG@5 from 0.5130 to 0.5530. The findings indicate that integrating Skill Authenticity into collaborative filtering can improve recommendation ranking while maintaining retrieval effectiveness, providing a more competency-aware approach to personalized learning in Moodle.

Keywords: collaborative filtering, skill authenticity, personalized learning, moodle, learning management system, ALS

Abstrak

Rekomendasi pembelajaran personal pada Learning Management System (LMS) *umumnya memanfaatkan pola interaksi mahasiswa, tetapi belum sepenuhnya mempertimbangkan kesenjangan kompetensi dan pengembangan keterampilan autentik. Penelitian ini mengusulkan* ACTS-CF (Authenticity-aware Collaborative Filtering)*, yaitu model rekomendasi yang mengintegrasikan data interaksi pembelajaran* Moodle, implicit feedback, Alternating Least Squares (ALS), *dan analisis kesenjangan berbasis* Skill Authenticity. *Data aktivitas pembelajaran Moodle ditransformasikan menjadi interaksi mahasiswa–materi, kemudian* ALS *digunakan untuk menghasilkan kandidat rekomendasi. Kandidat tersebut selanjutnya disempurnakan berdasarkan kesenjangan* Skill Authenticity *mahasiswa. Evaluasi dilakukan dengan membandingkan* ACTS-CF *dan* ALS *menggunakan* Precision@5, Recall@5, dan NDCG@5. *Hasil menunjukkan bahwa* ACTS-CF *mempertahankan* Precision@5 *sebesar 0,4667 dan* Recall@5 *sebesar 0,3525, serta meningkatkan* NDCG@5 *dari 0,5130 menjadi 0,5530. Hasil ini menunjukkan bahwa integrasi* Skill Authenticity *dapat meningkatkan kualitas pemeringkatan rekomendasi tanpa mengurangi efektivitas pengambilan rekomendasi.*

***Kata kunci**:* collaborative filtering, skill authenticity, personalized learning, moodle, learning management system, ALS.

I. INTRODUCTION

The rapid adoption of Learning Management Systems (LMS) has transformed higher education by providing flexible, interactive, and increasingly data-driven learning environments. Modern LMS platforms support not only the delivery of learning materials but also learner tracking, assessment, communication, collaboration, and the collection of learning interaction data [1][2]. These developments have expanded the role of LMS from conventional course management toward integrated environments that support learning analytics, personalization, and data-informed instructional decisions [1][2]. Every learner interaction, including accessing learning resources, completing assignments, participating in discussions, and engaging in collaborative activities, can therefore provide behavioral information that can be utilized to understand learner engagement and support personalized learning. As LMS platforms continue to accumulate heterogeneous learner interaction data, recommendation mechanisms are increasingly relevant for delivering learning pathways that are responsive to individual learner characteristics and needs [3].

Collaborative Filtering (CF) has become an important approach for personalized recommendation because it can identify learner preferences from interaction patterns and similarities among users [4]. In online and MOOC environments, CF has been applied to elicit learner preferences and provide personalized learning recommendations [4]. CF-based approaches have also been used to personalize learning materials by incorporating learner performance and historical interaction information, demonstrating their potential to improve the relevance of recommended educational resources [5]. Course recommendation research has further demonstrated the use of learning outcomes as an important basis for recommending courses to students, indicating that educational recommendation systems can move beyond simple content preference toward learning-oriented recommendation [3]. However, conventional CF primarily relies on behavioral similarity, historical preferences, or interaction patterns. Contextual information has therefore been investigated as an additional feature to improve recommendation decisions, suggesting that behavioral preference alone may not sufficiently represent the conditions under which educational recommendations should be generated [6].

This limitation is particularly important in competency-oriented higher education, where learning achievement should extend beyond the completion of digital learning activities to the development and demonstration of competencies that can be applied in realistic and professional contexts. Authentic learning provides an important foundation for addressing this requirement. Herrington and Oliver introduced an instructional design framework for authentic learning environments emphasizing authentic contexts and activities, access to expert performance, multiple perspectives, collaboration, reflection, articulation, coaching and scaffolding, and authentic assessment [7]. Similarly, the Five-Dimensional Framework for Authentic Assessment conceptualizes authenticity through task, physical context, social context, assessment form, and assessment criteria [8]. Recent research has further emphasized the role of authentic learning in connecting academic knowledge and skills with real-life and professional contexts [9]. Consequently, a recommendation system that relies solely on behavioral preference may recommend activities that learners are likely to engage with, while failing to prioritize activities that address their competency deficiencies or provide authentic opportunities for skill development.

To address this gap, this study proposes ACTS-CF (Authenticity-aware Collaborative Filtering), a personalized learning recommendation model that integrates Moodle learner interaction data, implicit feedback modeling, Alternating Least Squares (ALS), and Skill Authenticity-based competency gap analysis. The proposed approach transforms heterogeneous Moodle learning activities into learner–item interactions and applies implicit ALS to generate candidate recommendations. The candidate recommendations are subsequently refined by incorporating learners' Skill Authenticity profiles and competency gaps. In this way, the recommendation process considers both behavioral relevance and competency alignment rather than relying exclusively on historical learner preferences.

The primary contribution of this study is the development of a competency-aware collaborative filtering model that extends conventional ALS recommendation through Skill Authenticity-based recommendation refinement. Unlike recommendation approaches that primarily optimize behavioral relevance, ACTS-CF incorporates learners' competency needs into the recommendation ranking process. The resulting framework is designed to prioritize learning activities that simultaneously reflect learner interaction patterns and support authentic competency development. The effectiveness of the proposed model is evaluated against a baseline ALS model using Precision@5, Recall@5, and Normalized Discounted Cumulative Gain (NDCG@5) to determine whether Skill Authenticity-based refinement can improve recommendation ranking while maintaining recommendation retrieval effectiveness [10].

II. RESEARCH METHOD

A. ACTS-CF Recommendation Process

The ACTS-CF recommendation system uses learner interaction data collected from the Moodle learning environment. The data represent learner interactions with different learning activities, including SCORM, video, reading resources, assignments, journals, forums, collaborative activities, feedback, and peer-review activities. These heterogeneous records are consolidated and transformed into learner–item interaction data before being processed by the recommendation model.

The implementation follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) as a structured approach for processing and analysing the learning interaction data [11]. Within the ACTS-CF implementation, the process includes data preparation, interaction transformation, collaborative filtering, recommendation refinement, and recommendation evaluation.

The Moodle datasets required by the ACTS-CF Recommendation System are summarized in Table 1.

Table 1. Required Moodle Datasets for the ACTS-CF Recommendation System

Dataset	Moodle Table	Purpose
User	mdl_user	Learner profile information
Course	mdl_course	Course information
User Enrolment	mdl_user_enrolments	Learner enrolment records
Course Modules	mdl_course_modules mdl_course_modules_completion	Mapping of learning activities
SCORM Interaction	mdl_scorm mdl_scorm_scoes_track	Simulation and learning activity interactions
Assignment Submission	mdl_assign mdl_assign_submission	Assignment participation and submissions
Grade Records	mdl_grade_grades	Assessment results
Forum Interaction	mdl_forum_posts, mdl_forum_discussions	Discussion participation
Journal	mdl_journal mdl_journal_entries	Reflective learning activities
Resource Interaction	mdl_resource mdl_resource_interaction	Reading and video access history
Feedback	mdl_feedback_completed	Feedback participation
Workshop (Peer Review)	mdl_workshop_submissions, mdl_workshop_assessments mdl_group_members	Peer assessment and collaborative evaluation

Table 1 identifies the Moodle datasets required for recommendation generation and their corresponding data sources. These datasets provide the learner, course, activity, participation, completion, assessment, and interaction information required by the subsequent recommendation process. The dataset structure therefore provides the input basis for constructing the learner–item interaction representation.

After the required datasets have been prepared, they are uploaded to the ACTS-CF Recommendation System through the data-upload interface. The interface used for importing the Moodle datasets is presented in Figure 1.

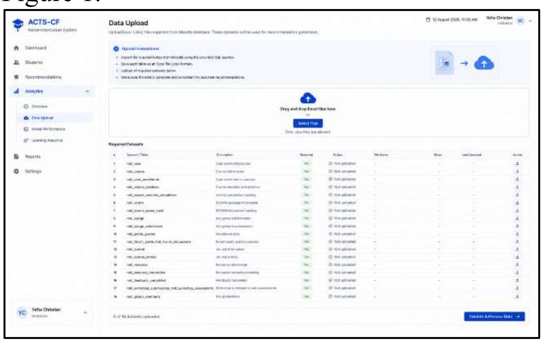

Figure 1. Moodle Dataset Upload Interface of the ACTS-CF Recommendation System

The uploaded datasets are validated before being processed by the recommendation engine. This validation ensures that the required data are available and can be integrated into the learner–item interaction structure used by the collaborative filtering process.

B. Implicit Feedback and ALS Collaborative Filtering

Following data validation, the Moodle interaction records are transformed into implicit learner–item interactions. Unlike explicit-rating recommendation, the ACTS-CF implementation interprets observed learner activities as implicit evidence of learner preference. This approach is appropriate for Moodle environments because learner preferences are generally represented through observable interactions such as accessing, completing, submitting, or participating in learning activities rather than through explicit ratings [12].

The resulting learner–item interaction data are processed using Alternating Least Squares (ALS) to obtain latent representations of learners and learning activities [12]. The ALS model estimates learner preferences based on historical interaction patterns and generates candidate learning activities for each learner.

The ALS-generated candidate recommendations subsequently become the input for the Skill Authenticity-based recommendation refinement. This refinement distinguishes ACTS-CF from conventional ALS-based recommendation by incorporating competency-oriented information into the recommendation ranking.

The integration of the ALS-based recommendation process with Skill Authenticity profiling, competency gap analysis, and recommendation ranking is presented in Figure 2.

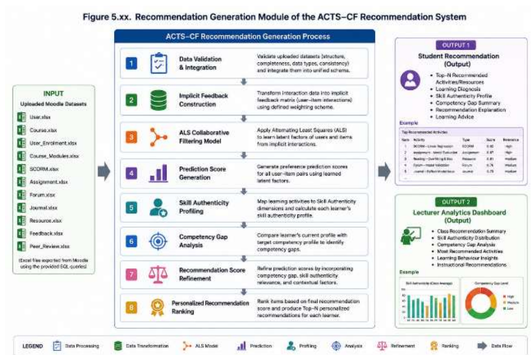

Figure 2. Recommendation System Recommendation Generation Module of the ACTS-CF Recommendation System

Figure 2 shows the integration of data validation, implicit-feedback construction, ALS collaborative filtering, Skill Authenticity profiling, competency gap analysis, and recommendation ranking within the ACTS-CF recommendation generation process.

C. Skill Authenticity-Based Recommendation Refinement

The main refinement stage of ACTS-CF is performed after the ALS candidate recommendations have been generated. The purpose of this stage is to prevent the recommendation process from relying solely on historical behavioural similarity and to incorporate the learner's competency development requirements.

The learner's Skill Authenticity profile is used to represent the learner's current competency-related characteristics across the six dimensions considered in the ACTS-CF implementation: Task, Physical Context, Social

Context, Accuracy, Outcome, and Meta-cognition.

The profile is subsequently used to identify competency gaps. A competency gap represents an area in which the learner requires additional learning activity exposure or development. The identified gaps are matched against the characteristics of the candidate learning activities generated by ALS.

For each candidate activity, a gap matching score is used to represent the degree of alignment between the learning activity and the learner's identified competency requirements. The ALS prediction score and gap matching score are then integrated to produce the final recommendation score.

The final recommendation score is used to rank the candidate learning activities. Consequently, the ACTS-CF recommendation ranking incorporates both behavioural relevance and competency alignment.

The resulting ranked recommendations are subsequently provided to the personalized recommendation interface and evaluated against the baseline ALS Collaborative Filtering model.

D. Personalized Recommendation Output

After the recommendation ranking has been generated, the ACTS-CF Recommendation System presents the resulting recommendations to the learner. The learner-facing interface provides the recommended learning activities together with information supporting the interpretation of the recommendations.

The student recommendation interface presents the learner's learning behaviour summary, Skill Authenticity profile, identified competency gaps, recommendation explanations, expected competency improvements, and personalized learning advice.

The resulting recommendation output and final ranking are presented and analysed in Section III.

E. Recommendation Evaluation Procedure

The effectiveness of ACTS-CF is evaluated by comparing the proposed model with the baseline ALS Collaborative Filtering model. Both models are evaluated using the same learner–item interaction data and recommendation setting. The principal difference is that ACTS-CF applies the Skill Authenticity-based competency refinement after ALS generates the candidate recommendations.

The evaluation uses Precision@5, Recall@5, and Normalized Discounted Cumulative Gain (NDCG@5), which were defined and justified in the Introduction. Precision@5 is used to assess the proportion of relevant activities within the five highest-ranked recommendations, while Recall@5 measures the proportion of relevant activities retrieved within the top five recommendation list. NDCG@5 is used to evaluate the ranking quality of the recommended activities.

III. RESULTS AND DISCUSSION

A. Final ACTS-CF Recommendation Output

Following the recommendation process described in Section II, ACTS-CF produces a ranked list of personalized learning activities. The final output contains the recommended item, activity type, ALS prediction score, Skill Authenticity gap matching score, final recommendation score, and recommendation rank.

Final recommendation ranking generated through this refinement process is presented in Figure 3.

FINAL ACTS-CF RECOMMENDATION OUTPUT

	userid	itemid	item_type	prediction_score	gap_matching_score	final_score	recommendation_rank
0	1831108	VD_RS018	Video	1.938562e-01	0.530417	2.948244e-01	1
1	1831108	VD_RS016	Video	1.181322e-01	0.530417	2.418175e-01	2
2	1831108	VD_RS017	Video	9.209090e-02	0.530417	2.235886e-01	3
3	1831108	RD_RS002	Reading	5.529880e-02	0.500000	1.887092e-01	4
4	1831108	RD_RS001	Reading	4.847288e-02	0.500000	1.839310e-01	5
5	1831108	VD_RS020	Video	2.023160e-02	0.530417	1.732871e-01	6
6	1831108	RD_RS008	Reading	3.085879e-02	0.500000	1.716012e-01	7
7	1831108	VD_RS011	Video	-1.592135e-02	0.530417	1.479801e-01	8

Figure 3. Final Recommendation Ranking Generated by ACTS-CF

Figure 3 shows that VD_RS018, categorized as a video activity, receives the highest recommendation rank with a final recommendation score of 0.2948244. The next two positions are also occupied by video activities, namely VD_RS016 and VD_RS017. Reading activities appear at ranks four and five through RD_RS002 and RD_RS001.

The ranking also illustrates that the final recommendation output is not represented solely by the prediction score. VD_RS011, for example, has a negative prediction score of −0.01592135, but remains in the recommendation list because its gap matching score contributes to the final recommendation score. This indicates that the competency-oriented refinement can influence the final ordering of candidate activities.

The resulting ranked output is consistent with the role of personalized educational recommender systems, in which recommendations are intended to prioritize learning resources according to individual learner characteristics and requirements rather than presenting an identical list of resources to all learners [13][14][15].

B. Recommendation Performance

The recommendation performance of the baseline ALS Collaborative Filtering model and the proposed ACTS-CF model was evaluated using Precision@5, Recall@5, and Normalized Discounted Cumulative Gain (NDCG@5). These metrics provide complementary measures of recommendation retrieval and ranking quality. NDCG considers the position of relevant items within a ranked list and therefore provides a ranking-sensitive measure of recommendation quality [13].

The comparison between ALS Collaborative Filtering and the proposed ACTS-CF is presented in Table 2.

Table 2. Recommendation Performance Comparison Between ALS Collaborative Filtering and ACTS-CF

Recommendation Model	Precision @5	Recall @5	NDCG @5
ALS Collaborative Filtering	0.4667	0.3525	0.513
Proposed ACTS-CF	0.4667	0.3525	0.5517

Table 2 shows that both models achieve a Precision@5 of 0.4667 and a Recall@5 of 0.3525. Therefore, the proposed ACTS-CF refinement does not change the retrieval performance of the baseline ALS model in terms of the top five recommendation list.

The main difference is observed in NDCG@5. The proposed ACTS-CF achieves an NDCG@5 of 0.5517, compared with 0.5130 for ALS Collaborative Filtering. The difference is 0.0387, corresponding to an improvement of approximately 7.54% relative to the baseline.

The unchanged Precision@5 and Recall@5 indicate that the proposed refinement maintains the ability of the baseline model to retrieve relevant learning activities. Meanwhile, the increase in NDCG@5 indicates an improvement in the ordering of those activities within the recommendation list. Since NDCG assigns greater importance to relevant items appearing at higher positions, the increase suggests that ACTS-CF produces a more effective ranking of the retrieved learning activities [16].

This result is particularly relevant to educational recommender systems because recommendation quality is not limited to whether relevant resources are retrieved but also concerns how those resources are prioritized for learners. Previous research on educational recommender systems has identified recommendation accuracy as an important evaluation dimension while also highlighting the need to consider broader educational and learner-related factors [13][14].

C. Distribution of Recommended Learning Activities

The generated recommendations were further analysed according to the types of learning activities included in the recommendation output. This analysis provides an additional perspective on the composition of the recommendations generated by ACTS-CF.

The distribution of recommended learning activities is presented in Figure 4.

```
==========================================================
STEP 30.1 : RECOMMENDED LEARNING ACTIVITY DISTRIBUTION
==========================================================
```

	item_type	Frequency	Percentage
6	Reading	100	31.75
8	Video	99	31.43
5	Peer Review	25	7.94
0	Assignment	22	6.98
7	SCORM	22	6.98
1	Collaborative Task	20	6.35
4	Journal	15	4.76
2	Feedback	10	3.17
3	Forum	2	0.63

Figure 4. Distribution of Recommended Learning Activities Generated by The Proposed ACTS-CF Framework

Figure 4 shows the distribution of recommended activities across the available Moodle learning activity types. The result demonstrates the types of learning activities selected by ACTS-CF rather than limiting recommendations to a single category of learning resource.

The use of heterogeneous learning resources is relevant to educational recommender systems because personalized recommendations can involve different forms of learning materials and activities according to learner needs and the educational context [13][14]. Consequently, the activity distribution provides complementary evidence to the ranking metrics by showing the characteristics of the learning resources selected by the recommendation system.

D. Distribution by Experiential Learning Stage

The generated recommendations were further examined according to the stages of Experiential Learning. The corresponding distribution is presented in Figure 5.

```
==========================================================
STEP 30.2 : EXPERIENTIAL LEARNING STAGE DISTRIBUTION
==========================================================
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	experiential_stage	Frequency	Percentage
2	Concrete Experience	143	45.40
0	Abstract Conceptualization	110	34.92
1	Active Experimentation	45	14.29
3	Reflective Observation	17	5.40

Figure 5. Distribution of Recommendations by Experiential Learning Stage

Figure 5 presents the distribution of the recommended learning activities across the experiential learning stages. The analysis provides an additional perspective on the learning characteristics represented in the recommendation output.

The distribution demonstrates how the recommended activities are represented across the experiential learning cycle. This analysis complements the quantitative recommendation evaluation by examining the pedagogical characteristics of the generated recommendations rather than focusing exclusively on recommendation accuracy.

E. Distribution by Skill Authenticity Dimension

The recommendation outputs were also analysed according to the Skill Authenticity dimensions addressed by the recommended learning activities. The ACTS-CF implementation considers six dimensions: Task, Physical Context, Social Context, Accuracy, Outcome, and Meta-cognition.

The resulting distribution is presented in Figure 6.

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====================================================
STEP 30.3 : SKILL AUTHENTICITY DISTRIBUTION
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	skill_authenticity	Frequency	Percentage
2	Outcome Authenticity	192	35.62
5	Task Authenticity	163	30.24
0	Accuracy Authenticity	100	18.55
1	Meta-Cognitive Authenticity	45	8.35
3	Physical Context Authenticity	22	4.08
4	Social Context Authenticity	17	3.15

Figure 6. Distribution of Recommendations by Authenticity Dimension

Figure 6 shows the distribution of the recommended learning activities across the Skill Authenticity dimensions. This analysis provides evidence of the competency-oriented characteristics represented in the recommendation output.

The analysis is important because educational recommender systems have increasingly been investigated in relation to learner needs and educational context rather than solely historical preference [13][14][15]. In the context of ACTS-CF, the Skill Authenticity distribution provides an additional means of examining whether the generated recommendations correspond to different competency-oriented learning requirements.

F. Student Recommendation Output

The final ACTS-CF recommendations are presented to learners through the personalized recommendation interface. The interface provides the learner with the generated recommendations and supporting information related to learning behaviour and competency requirements.

The personalized recommendation output is presented in Figure 7.

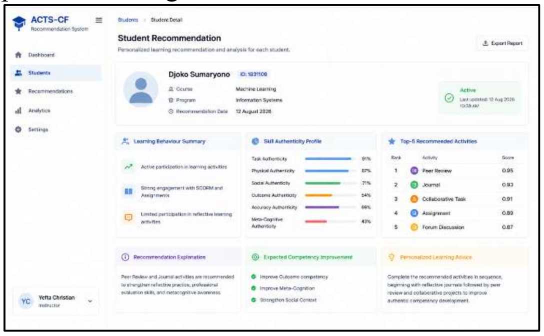

Figure 7. Student Recommendation Interface of the ACTS-CF Recommendation System

Figure 7 presents the learner-facing recommendation output generated by ACTS-CF. The interface provides personalized recommendation information together with the learner's learning behaviour summary, Skill Authenticity profile, identified competency gaps, recommendation explanations, expected competency improvements, and personalized learning advice.

The presentation of personalized recommendations is consistent with the broader objective of educational recommender systems, which is to support learners by providing recommendations adapted to their individual learning context and requirements [13][14][15]. In ACTS-CF, this personalized output complements the ranking results by providing learners with contextual information associated with the recommended activities.

G. Discussion

The results demonstrate that the proposed ACTS-CF model improves the ranking quality of ALS-based recommendations while maintaining the retrieval performance of the baseline model. The identical Precision@5 and Recall@5 values indicate that the refinement does not reduce the ability of the system to retrieve relevant learning activities. At the same time, the increase in NDCG@5 from 0.5130 to 0.5517 demonstrates an improvement in the ordering of the recommended activities.

The improvement in NDCG@5 is particularly important because ranking-sensitive evaluation considers the position of relevant items within the recommendation list [16]. Therefore, the result suggests that the competency-aware refinement affects the prioritization of the retrieved activities rather than simply increasing the number of relevant activities retrieved.

The final recommendation output provides an example of this ranking behaviour at the learner level. The recommendation list contains different learning activity types and provides the prediction score, gap matching score, final score, and ranking position. The output therefore demonstrates how the recommendation results can be examined at the individual learner level in addition to aggregate evaluation using recommendation metrics.

The distribution analyses provide three additional perspectives on the recommendation output: learning activity type, Experiential Learning stage, and Skill Authenticity dimension. These analyses are important because educational recommender systems operate within a learning context in which the characteristics of recommended resources can be as important as their predictive relevance [13][14].

The Skill Authenticity-oriented analysis further distinguishes ACTS-CF from a recommendation approach based solely on historical behavioural similarity. Personalized learning recommender systems increasingly consider learner characteristics, learning needs, and contextual information when generating recommendations [13][14][15]. In ACTS-CF, these considerations are reflected in the competency-oriented characteristics of the recommendation output.

Overall, the findings indicate that ACTS-CF provides a competency-aware extension of ALS Collaborative Filtering. The principal quantitative improvement is observed in NDCG@5, which increases by approximately 7.54% relative to the baseline while Precision@5 and Recall@5 remain unchanged. The results therefore support the use of Skill Authenticity-based refinement as a mechanism for improving recommendation ranking while preserving the retrieval effectiveness of the underlying collaborative filtering model.

IV. CONCLUSION

This study presented ACTS-CF, an authenticity-aware collaborative filtering recommendation model designed to support personalized learning activity recommendations within the Moodle learning environment. The proposed approach extends conventional ALS-based collaborative filtering by incorporating Skill Authenticity-based competency gap analysis into the recommendation refinement process. The integration enables learning activities to be ranked not only according to learner–item interaction patterns but also according to their alignment with identified competency-related learning needs.

The experimental results demonstrate that the proposed ACTS-CF model maintains the retrieval performance of the baseline ALS Collaborative Filtering model while improving the quality of the recommendation ranking. Both models achieved a Precision@5 of 0.4667 and a Recall@5 of 0.3525. However, NDCG@5 increased from 0.5130 for the baseline ALS model to 0.5517 for ACTS-CF, representing an improvement of approximately 7.54%. This result indicates that the Skill Authenticity-based refinement improves the prioritization of relevant learning activities within the recommendation list without reducing the baseline retrieval performance.

The final recommendation outputs further demonstrate the operation of the proposed model at the individual learner level. ACTS-CF produces ranked learning activities together with prediction scores, gap matching scores, final recommendation scores, and recommendation ranks. The resulting recommendation outputs can therefore provide a more competency-oriented interpretation of personalized learning recommendations than a conventional collaborative filtering ranking based solely on historical learner interactions.

Additional analysis of the recommendation outputs examined the distribution of recommended learning activities, Experiential Learning stages, and Skill Authenticity dimensions. These analyses provide complementary evidence regarding the characteristics of the learning activities selected by ACTS-CF and demonstrate that the recommendation output can be examined not only from a quantitative ranking perspective but also from pedagogical and competency-oriented perspectives.

Overall, the findings indicate that ACTS-CF provides a feasible competency-aware extension of ALS Collaborative Filtering for personalized learning recommendation in Moodle. Its main contribution is the integration of behavioral recommendation with Skill Authenticity-based competency refinement, resulting in improved ranking quality as reflected by NDCG@5. The findings also support the broader objective of educational recommender systems to provide recommendations that consider learner needs and educational context rather than relying exclusively on historical interaction patterns [13][14][15].

For future work, the ACTS-CF model can be further evaluated using larger and more diverse learner populations, longer learning periods, and additional Moodle courses. Future studies may also investigate online or real-time recommendation updates, alternative collaborative filtering algorithms, and more comprehensive pedagogical evaluation involving learner engagement and learning achievement. Such evaluation would provide additional evidence regarding the practical effectiveness of competency-aware recommendation beyond offline ranking performance.

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