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Designing a Hybrid Learning Resource Recommender Model using Learning Object Rating Algorithm for Adaptive Learning

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ABSTRACT

E-learning has become a key component of modern education that provides access to digital learning resources. However, the overwhelming volume of content can make it difficult for learners to find materials suited to their needs. This has led to a growing demand for adaptive learning, which personalises content based on learner characteristics. To support this, e-learning platforms adopt recommender systems through machine learning techniques. While effective, these systems often depend heavily on historical data, such as user ratings and interactions, to generate meaningful recommendations. This dependency introduces a significant challenge known as data sparsity, where insufficient interaction data limits the model’s ability to provide accurate recommendations. This study addresses this challenge by proposing a hybrid learning resource recommender model that combines collaborative and content-based filtering and introduces the Learning Object Rating Algorithm (LORA). This hybrid approach reduces reliance on user-generated ratings by allowing LORA to generate initial ratings based on the learners’ profiles and resource characteristics, thus filling gaps in interaction history. The model was evaluated through experiments assessing its prediction accuracy and relevance of recommendations by using Mean Absolute Error (MAE), Precision, and Recall. Additionally, the performance of the proposed hybrid model was compared with existing hybrid models through a comparative analysis. Results revealed that the proposed model outperformed previous hybrid recommender models, generating better prediction accuracy and recommendation relevance. The integration of a hybrid approach and LORA enabled the model to generate ratings based on learning styles and resource characteristics, mitigating the data sparsity issue and reducing dependence on user-generated ratings.

Keywords: Adaptive learning, collaborative filtering model, content-based filtering model, hybrid recommender model, learning object rating algorithm.

INTRODUCTION

The adoption of e-learning has contributed to a significant increase in online educational resources. Online learning platforms now host an extensive repository of learning materials, including lectures, videos, articles, assessments, and interactive simulations, containing topics from academic and professional subjects (Ali et al., 2021; Karthika et al., 2020; Zaoudi & Belhadaoui, 2020). Nonetheless, this abundance of resources also presents a new challenge. Learners may struggle to efficiently identify learning resources that might align with their specific learning objectives and needs. This challenge has led to the integration of recommender models within e-learning environments. These machine learning models utilise learner characteristics such as learning styles, behaviours, or profiles to navigate the vast array of learning resources and provide personalised recommendations (Alajlani et al., 2024; Mirata & Bergamin, 2023; Muñoz et al., 2022; Soliman et al., 2025).

However, it is important to understand that recommender models are also highly dependent on historical interactions between the students and the learning resources. These interactions are usually evident in the form of ratings that students provide, which are interpreted as indicators of students' preferences for the learning materials. Typically, students are required to rate or interact with each learning resource available in an e-learning system. These ratings are then gathered from various courses, semesters and students. Once this data is available, recommender models are trained to analyse and identify how likely a student prefers a particular learning material based on learning styles (Abadia & Liu, 2021; Sihombing et al., 2020). Consequently, without a significant amount of these ratings, the performance of the recommender model is greatly affected, thus making it challenging to build an accurate learning resource recommender model. This challenge in recommender models is called data sparsity, which affects the accuracy of the model. The higher the data sparsity, the less accurate the model becomes (Jeevamol & Renumol, 2021; Joy & Pillai, 2022; Tan et al., 2020).

To address this challenge, different recommender modelling techniques have been explored from previous studies. Among these methods is the hybrid recommender modelling technique, in which two or more recommender models are combined, such as a content-based filtering (CBF) model, a collaborative filtering (CF) model, among others (Kaiss et al., 2022; Ulfa et al., 2019; Wan & Niu, 2020). These hybrid recommender models are designed to leverage the strengths of multiple recommender models and alleviate each other's weaknesses. However, despite these efforts, the data sparsity persists when the interactions between students and learning resources are minimal or insufficient to generate meaningful recommendations. In many cases, students are required to interact with or provide ratings for many available learning resources, but obtaining such interactions consistently can be challenging. Hence, ensuring that students will provide ratings or engage with every learning resource is seemingly difficult to accomplish, making it challenging to gather enough data to train an accurate and effective recommender model.

Therefore, the purpose of this study is to design and evaluate a hybrid learning resource recommender model that introduces an algorithm that calculates the ratings between learners and learning resources based on learning style and learning resource characteristics. This algorithm is intended to alleviate the data sparsity problem and to enable the recommender model to make accurate personalised recommendations without requiring direct interaction with students. This approach focuses on exploring the potential of reducing reliance on student-provided ratings to support the recommendation process.

RELATED WORKS

Theory of Learning Styles

In the educational context, "learning styles" refer to unique traits or approaches that define how a student engages and processes information within the learning process. These approaches are categorised by various learning style theories, which provide frameworks for understanding how different students approach learning tasks (A. Hidayat et al., 2021; Sensuse et al., 2020). Learning styles are also referred to as cognitive or intellectual styles, reflecting the processes through which students perceive, organise, process, and recall information. Numerous studies have examined learning styles to understand their role in the learning process. Students who can recognise their own learning style may interact with learning materials in ways that correspond to their natural preferences for processing information. This self-awareness can affect the methods students use to engage with learning tasks (Dantas & Cunha, 2020; Hasibuan et al., 2019; Shrestha & Pokharel, 2021). Various learning style theories have been developed to classify the different attributes that make up these styles. Each theory provides a unique framework for educators to consider when designing instructional strategies and learning materials. Some of the most widely recognised learning style theories, which serve as foundational models in the study of personalised education, are shown in Table 1.

Table 1

Commonly Adopted Learning Style Theories for Personalised Learning

Learning Style Theories	Classifications and Dimensions
Felder-Silverman Learning Style Theory (1988)	Input (visual or verbal), Processing (active or reflective), Perception (sensing or intuitive), Understanding (sequential or global)
Fleming & Mill Learning Style Theory (1992)	Visual, Aural, Reading/Writing, and Kinesthetic (VARK)
Kolb Experimental Learning Theory (1943)	Divergers, Assimilators, Convergers and Accommodators
Myers & Briggs Type Indicator Learning Style Theory (1943)	Extraversion or Introversion, Judging or Perceptive, Feeling or Thinking, Sensing or Intuition

In a comparative study by Zine et al. (2019), they sought to answer the question: "Which learning style model is most suitable for use in personalised learning?". Among the commonly adopted learning style theories, the findings of the study revealed that the Felder-Silverman Learning Style Model (FSLSM) is the most effective for personalised learning. The research paper argued that the Index of Learning Style (ILS) instrument, derived from FSLSM, has undergone extensive examination through multiple studies and has demonstrated effectiveness in designing instructional materials, teaching approaches, and learning assessments that align with learning styles. Additionally, this instrument can easily be interpreted, and the dimensions can be adjusted in different educational settings. The ILS questionnaire consists of 44 questions, which share the same content but are expressed differently. It helps understand how learners engage, process information, receive information, and organise knowledge.

Furthermore, understanding learning styles has evolved into a fundamental factor in the design and implementation of adaptive learning into educational practices (Katsaris & Vidakis, 2021; Khamparia & Pandey, 2020; Maaliw III, 2020). The model's relevance and practical utility are further highlighted by findings from systematic literature reviews on adaptive learning conducted by Afini Normadhi et al. (2019), which emphasise its extensive adoption in educational research and practice. One of the key strengths of FSLSM lies in its explicit modelling technique, which provides a structured approach for categorising learners based on their cognitive preferences. The FSLSM has emerged as the predominant method for identifying learning styles, as supported by several studies (Benitez, 2023; N. Hidayat & Afuan, 2021; Joshi, 2020; Nafea et al., 2019; Sensuse et al., 2020; Sihombing et al., 2020; Valencia Usme et al., 2023).

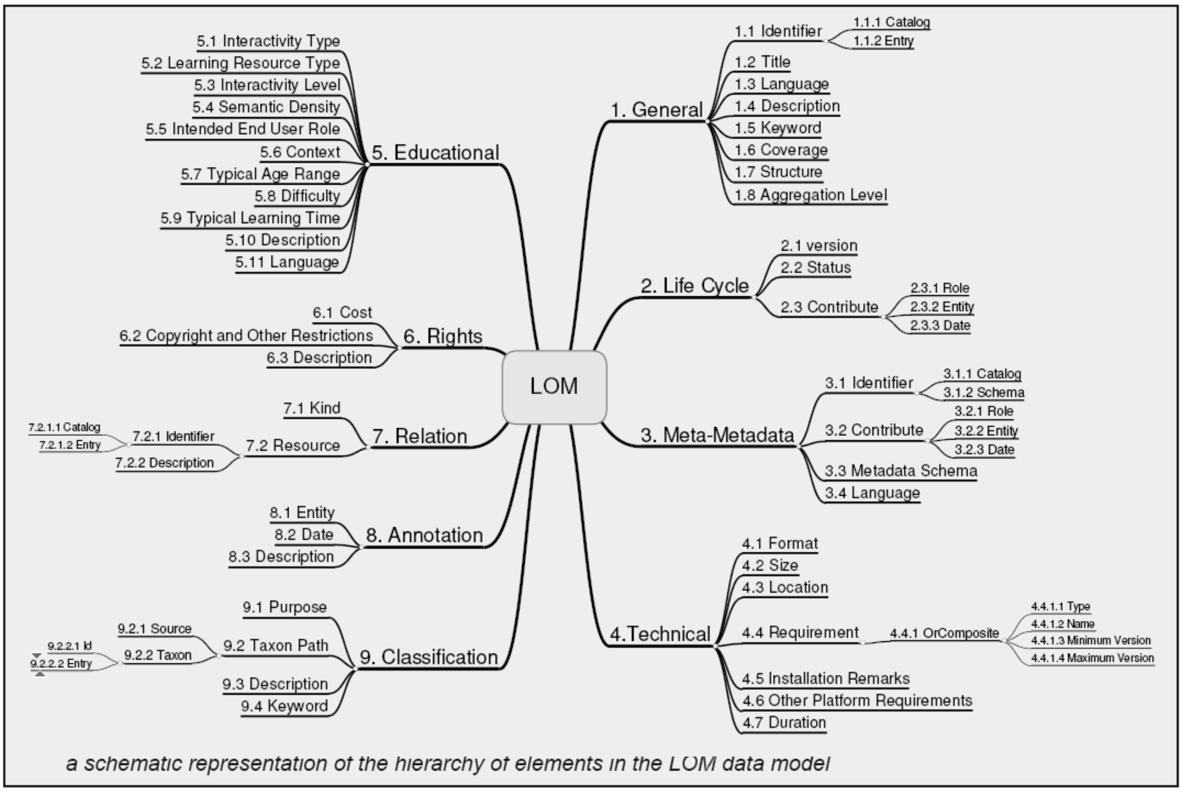
Learning Objects Metadata

While learning styles are crucial elements in personalised learning, learning resources are also one of the key elements to provide personalisation of learning. Learning objects (LOs) can be described as any digital learning resource that is independent and can be reused (Apoki et al., 2020; Da Silva et al., 2017). These online learning resources are autonomous segments of educational information, designed to function independently and to be applicable across various learning contexts. In recommender systems, LOs play a crucial role in supporting personalised learning by aligning which LOs are suited for a particular learning style. A key characteristic of LOs is their capacity to be described, classified, and organised through metadata. Each learning object contains descriptive information known as Learning Object Metadata (LOM), which serves to catalogue and identify the object within a larger digital repository (Da Silveira Dias & Wives, 2018; Deldjoo et al., 2020; İnce et al., 2019). This descriptive feature enables recommender models to identify relevant learning resources that meet specific learning needs quickly.

Many international standards are developed to maintain consistency and standardisation in the design, description, and organisation of LOs. They ensure that LOs follow a common framework, making them easily shareable and usable across different educational platforms. The most well-known metadata standards for LOs include international guidelines established by organisations such as the Institute of Electrical and Electronics Engineers (IEEE), including LOM (IEEE Learning Technology Standards Committee, 2002), shown in Figure 1. The use of the LOM played a crucial role in enabling the classification, personalisation, and recommendation of LOs (Jeevamol & Renumol, 2021; Joy & Pillai, 2022; Raj & Renumol, 2018; 2022). An examination of existing literature indicates that certain metadata elements are frequently utilised in the design of these educational resources. Notably, the interactivity type, interactivity level, and learning resource type metadata fall under the educational category, along with the format metadata from the technical category and the structure metadata from the general category, emerged as the most adopted elements. These metadata serve to describe the fundamental composition and characteristics of e-learning resources. Furthermore, previous studies have demonstrated that the FSLSM can be effectively mapped with LOM. The alignment of the metadata with the learning style model has shown promising results in providing personalised learning object recommendations and designing recommender models (Y. Chen et al., 2018; Martin et al., 2020; Soler Costa et al., 2021; Yang et al., 2022).

Figure 1

Schematic Representation of the Elements in IEEE LOM



Recommender Models

Recommender models are described as machine learning models that are designed to provide personalised recommendations based on users' preferences or characteristics to make an informed decision. Commonly, recommender models use a variety of data to present recommendations, including historical interactions, user-to-user preferences or user-to-item preferences. In the context of personalised learning, the aim primarily focuses on providing relevant learning resources to the students based on their preferences, learning styles, objectives or interests to mitigate the negative impacts of the over-choice burden (Amin et al., 2023; Clemente et al., 2022; Deldjoo et al., 2020).

Previous studies have demonstrated the application of hybrid recommender methods for learning resource recommendations. These studies include the application of CF, CBF, and hybrid filtering methods, which combine two or more techniques to enhance the accuracy and relevance of learning resource recommendations. However, despite the promising results, there are notable limitations. The complexity of implementing hybrid recommender systems is still limited by the data sparsity problem, which results in the recommender system struggling to make accurate recommendations with limited interaction data, and this remains a significant challenge. Addressing these limitations is crucial for the continued development and effectiveness of hybrid recommender models (Baidada et al., 2021; Ezaldeen et al., 2022; Hui et al., 2023; Jeevamol & Renumol, 2021; Tahmasebi et al., 2019; Wan & Niu, 2020).

CF Models

CF is a widely adopted technique in recommender systems, due to its ability to generate personalised recommendations by integrating users' historical interactions and ratings. In academic contexts, the goal is to recommend learning resources that students are likely to prefer based on the preferences of other students with similar learning patterns. It works on the principle that users with similar past preferences are likely to share future preferences. By analysing users' ratings of learning resources, it identifies patterns and similarities among users to generate personalised recommendations. Since it relies solely on user interactions and ratings, without requiring domain-specific knowledge, it is especially valuable in personalised learning (Deng et al., 2018; Martins et al., 2020; Wang & Fu, 2021; Wei et al., 2020).

However, CF is not without its challenges. One significant limitation is the cold start problem, where the system struggles to make recommendations for new students or new learning resources due to insufficient interaction data. This lack of prior data affects the model's ability to provide meaningful recommendations, especially in the early stages of a user's or item's introduction. Moreover, CF lacks the ability to recognise the intrinsic characteristics of learning resources and often faces difficulties in handling sparse data, where most users have rated only a small subset of the available learning resources. This sparsity can undermine its ability to determine similarities between users and provide high-quality recommendations (Afoudi et al., 2021; Aziz et al., 2021; Ezaldeen et al., 2022; Hasibuan et al., 2023; Nafea et al., 2019). While CF remains a widely used approach in learning resource recommender, addressing its inherent limitations is essential for enhancing its overall effectiveness and scalability. These limitations can be mitigated by integrating other approaches, such as CBF.

CBF Models

CBF is a machine technique used in recommender systems to suggest items to users based on the characteristics of the items and the preferences of the users. The objective of this method is to provide personalised learning resource recommendations by analysing learning object descriptions and the learner's characteristics, such as learning styles (Lops et al., 2019; Riyahi & Sohrabi, 2020; Shu et al., 2018). The assumption is that items similar to those a user has preferred in the past can be effectively recommended in the future. The similarity is determined by analysing item attributes, which is crucial in the recommendation process. Additionally, the user's characteristics are equally important in such recommender systems.

By designing a detailed user profile, the model can assess the similarities between the user and others. In learning resource recommender systems, CBF provides a distinct advantage by recommending LOs that are particularly relevant to each individual student, based on their specific interests and preferences. This method is especially useful for new students who have little or no prior interaction history within the system. One of the strengths of CBF is that it does not suffer from the cold start problem, as it can generate recommendations solely based on the attributes of the LOs themselves, without needing prior user interaction data (Amin et al., 2023; Joshi, 2020; Lin et al., 2019).

However, CBF also has its limitations. A notable weakness is its tendency to produce recommendations that lack diversity. Since the model primarily suggests items that are similar to those the student has already shown interest in, it can lead to a filter bubble, where users are exposed to a narrow range of content that reinforces their existing preferences. This lack of variety in recommendations can reduce the overall effectiveness of the model, as it may limit students' exposure to new and different types of learning resources. Furthermore, this model requires comprehensive information about each learning object to function optimally. While CBF excels at providing personalised recommendations based on the attributes of learning resources, there is a clear need to enhance the diversity of these recommendations to avoid the filter bubble effect (Jeevamol & Renumol, 2021; Lops et al., 2019; Niyigena & Jiang, 2020).

Hybrid Recommender Models

While these CF and CBF models have their distinct advantages, they also come with significant limitations. A hybrid recommender approach is an advanced approach in recommender systems that seeks to combine multiple recommendation techniques, most commonly CBF and CF, into a unified recommender framework. This integration allows hybrid models to adopt the strengths of each method while simultaneously addressing their respective weaknesses. The summary of the strengths and weaknesses of both CBF and CF recommenders is presented in Table 2.

Table 2

Strengths and Weaknesses of Collaborative and CBF Models

Recommender Models	Strength	Weakness
CF Model	Does not require item features to enable recommendations.	Data sparsity. The interactions and ratings are not sufficient to make recommendations. Cold-Start problem. Cannot recommend an item to a user who has not been previously.
CBF Model	Does not suffer from the cold-start problem. Does not require the user's features; thus, it is resilient to users' behaviour.	New item Issue. New items with little to no history of interactions are challenging to recommend, as they require extensive item features to identify similarities with existing items.

With this, one of the most significant strengths of building hybrid recommenders lies in their ability to provide more accurate recommendations by combining the recommendations from CBF with the crowd-sourced insights derived from CF. CBF analyses the attributes of learning resources and matches them to users based on their personal preferences. In contrast, CF relies on the behaviour and preferences of similar users to generate recommendations. This multi-approach enables hybrid recommender systems to capture both the nuances of individual student needs and the general trends among identified groups (Riyahi & Sohrabi, 2020; Shanshan et al., 2021; Tarus et al., 2018).

Nonetheless, despite their many advantages, hybrid recommender models, like all recommender models, suffer from data sparsity problems due to over-reliance on user-generated interactions and ratings. This lack of data can significantly limit the system's ability to make accurate recommendations, as both CF and CBF, as well as hybrid recommender methods, rely on a substantial amount of interaction data to function effectively. Although CBF can provide recommendations for new items based on their attributes, CF requires a higher volume of user interactions to generate reliable recommendations. Even with a hybrid modelling approach, recommender models from previous studies still rely on the students to provide the ratings for the model to make recommendations (Jeevamol & Renumol, 2021; Niyigena & Jiang, 2020; Shanshan et al., 2021; Tarus et al., 2018). The challenge of ensuring that students provide ratings or engage with every learning resource is seemingly difficult to accomplish, thus making it challenging to design an effective recommender model.

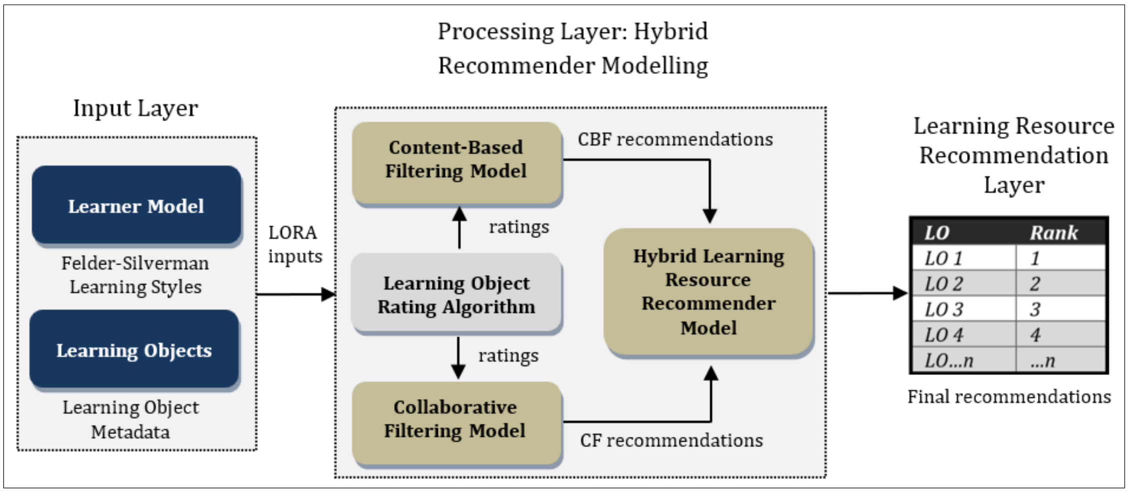
The more interactions and ratings a user has with learning resources, the more accurate the recommendations will become. Thus, ensuring robust interaction data remains a critical factor for optimising the performance of hybrid recommender systems. Addressing issues of data sparsity will be key to maximising the potential of hybrid recommender models. (Ezaldeen et al., 2022; Jeevamol & Renumol, 2021; Lin et al., 2019; Riyahi & Sohrabi, 2020; Tarus et al., 2018). Nonetheless, by combining the best features of multiple recommendation approaches, the hybrid approach provides a more accurate and adaptable solution for delivering personalised learning.

METHODOLOGY

This section describes the research methods, modelling techniques, and evaluation process for the proposed hybrid learning resource recommender model. Results are presented using statistical methods, including tables and graphs, to examine model performance across different recommendation scenarios. Figure 2 summarises the model's functionality. The model has two main layers: the input layer, which includes the representation of student learning styles using the Felder-Silverman Learning Style Model and LOs using the IEEE LOM Standard; and the processing layer, which includes the Learning Object Rating Algorithm (LORA) to support CBF and CF by calculating ratings based on learning styles and metadata without requiring prior student interaction. CBF and CF use cosine similarity and Pearson correlation, respectively, to recommend LOs. Both models are combined into a hybrid recommender model evaluated using Mean Absolute Error (MAE), Precision, and Recall. Results are then compared with existing hybrid recommender models.

Figure 2

The Proposed Hybrid Learning Resource Recommender Model using LORA



Experimental Setup

To design the learner model, the ILS questionnaire from FSLSM was adopted. The ILS questionnaire consists of 44 multiple-choice questions that are divided into 11 questions for each of the four (4) dimensions, with two possible answers (e.g., “A” or “B”) each representing the possible learning styles as illustrated in Table 3. The intensity of the ILS for each dimension can vary between -11 and +11. (Leka & Kika, 2018; Sensuse et al., 2020). A total of 651 computing students from Marinduque State University, the Philippines, participated in the distributed instrument. The first experiment was conducted from the beginning of the Academic Year 2024-2025 within 6 months.

Additionally, students are only required to provide their student ID number and not their real identity to enable data management and analysis while ensuring accuracy in learner profile identification. All collected data from the questionnaire were processed following strict data protection measures to uphold confidentiality and security. This study complies with the provisions outlined in Republic Act 10173 - Data Privacy Act of 2012, ensuring that student information remains protected and is utilised solely for research and academic purposes.

Table 3

ILS Questionnaire from Felder-Silverman Learning Style Model

Dimensions	Learning Styles	Question Items
Processing	Active or Reflective	1,5, 9, 13, 17, 21, 25, 29, 33, 37, 41
Perception	Sensing or Intuitive	2, 6, 10, 14, 18, 23, 26, 30, 32, 34, 38
Input	Visual or Verbal	3, 7, 11, 15, 19, 24, 27, 31, 35, 39, 43
Understanding	Sequential or Global	4, 8, 12, 16, 20, 25, 28, 32, 36, 40, 44

To calculate the ILS, the steps are as follows: (1) Tally the scores for each of the alternative answers (2) calculate the sum of all the results for each alternative answers (total score of A, and total score of B) for each given dimensions, for example in the processing dimension, if A=-7 and B=4, (3) add the total score of “A” and the total score of “B”. (4) To get the ILS, in this example, the sum of score from A=-7 and B=4 is -3A, which means the identified learning style is “Active” (El-Bishouty et al., 2019; Felder & Silverman, 1988; Leka & Kika, 2018).

LORA Design Process

In designing the proposed LORA, the design of a learning object model is required. This study adopted the IEEE LOM Standard. From the Educational category, three metadata were selected: Interactivity Type (IT), Learning Resource Type (LRT), and Interactivity Level (IL). From the Technical category, the Format (F) metadata was chosen. Additionally, two metadata from the General category were included: Structure (S), which describes the organisational structure of the learning object, and Keyword (K), which provides an overall classification of the learning object. The value space for the Keyword (K) metadata is defined as follows: overview, concept, fact, procedure, process, principle, summary, and assessment. These metadata are subsequently mapped to the dimensions of learning styles. Table 4 presents the associations between the learning styles from FSLSM and the selected LOM.

Table 4

The Association between LOs' Metadata and Learning Styles

Learning Styles	LOM	Study
Active or Reflective	Interactivity Type, Interactivity Level, Learning Resource Type, Format	Ahmed & Hina (2019), Ferreira et al. (2017), Sensuse et al. (2020)
Sensing or Intuitive	Keyword, Format, Learning Resource Type	
Visual or Verbal	Format, Learning Resource Type	Da Silva et al. (2017), Raj and Renumol (2018)
Sequential or Global	Keywords, Structure	

The metadata elements Interactivity Type, Interactivity Level, Learning Resource Type, and Format are strongly correlated with active and reflective learning in the processing dimension, as they describe the interaction and behaviour between students and LOs, reflecting preferences for active or passive learning. The metadata elements General, Format, and Learning Resource Type are closely linked to sensing and reflective learning in the perception dimension, as they define the type and format of LOs that align with students' preferences. Additionally, Format and Learning Resource Type are associated with visual and verbal learning in the input dimension, describing how LOs can be presented in visual, textual, or auditory forms. Finally, General and Structure metadata are strongly linked to sequential and global learning in the understanding dimension, as they capture the overall structure of the LOs (Cardozo et al., 2024; A.-H. Chen & Ahmad Nazri, 2021; Katsaris & Vidakis, 2021; Magulod, 2019; Sensuse et al., 2020).

Mapping the LOM Value Spaces with Learning Styles

Based on the identified associations between learning styles and LOM, Table 5 maps the metadata value spaces to their corresponding learning styles using Boolean values (1 or 0), where 1 indicates a recommended linkage and 0 indicates otherwise.

Table 5

The Mapping of Metadata Value Spaces and Learning Styles

Metadata	Value Space	Processing		Perception		Input		Understanding	
		Act.	Ref.	Sen.	Int.	Vis.	Ver.	Seq.	Glob.
Learning Resource Type	Exercise	1	0	0	0	0	0		
	Simulation	1	0	1	0	1	0		
	Questionnaire	1	1	0	0	0	1		
	Diagram	1	1	0	1	1	0		
	Figure	1	0	1	0	1	0		
	Graph	1	1	1	0	1	0		
	Index	0	1	1	0	0	1		
	Slide	1	1	1	0	1	0		
	Table	0	1	1	0	0	1		
	Narrative Text	0	1	0	1	0	1		
	Exam	1	1	1	0	0	1		
	Experiment	1	1	1	0	1	1		
	Problem Statement	1	0	0	1	1	1		
	Self-Assessment	0	1	0	1	0	1		
	Lecture	1	1	0	0	0	1		

(continued)

Metadata	Value Space	Processing		Perception		Input		Understanding	
		Act.	Ref.	Sen.	Int.	Vis.	Ver.	Seq.	Glob.
Interactivity Type	Active	1	0						
	Expositive	0	1						
	Mixed	1	1						
Interactivity Level	Low	0	1						
	Medium	1	1						
	High	1	0						
Keyword	Overview			1	1			0	1
	Concept			0	1			1	1
	Fact			1	0			0	1
	Procedure			1	0			1	0
	Process			1	0			1	0
	Principle			0	1			0	1
	Summary			1	1			0	1
	Assessment			1	1			1	1
Format	Video	1	0	1	0	1	1		
	Audio	0	1	0	1	0	1		
	Image	0	1	1	1	1	0		
	Text	0	1	0	1	0	1		
	Application	1	0	1	0	1	1		
	Form	1	0	0	0	0	1		
Structure	Atomic							0	1
	Collection							0	1
	Networked							0	1
	Hierarchical							1	0
	Linear							1	0

Active learners prefer highly interactive environments; thus, their materials should integrate interactivity types classified as active or mixed, with interactivity levels from medium to high, including exercises, simulations, experiments, and problem statements. Reflective learners prefer passive learning experiences, so resources should feature expositive or mixed interactivity types with low to medium interactivity levels. Sensing type learners prefer practical, realistic information and prefer LOs with facts, procedures, and clear instructions, such as experiments, questionnaires, diagrams, and slides in video or image formats. Intuitive learners prefer abstract and conceptual content, preferring overviews, principles, and summaries delivered in text, image, or audio formats.

Subsequently, visual and verbal learning reflect preferences for information presentation. Visual learners favour video or image-based resources such as simulations, diagrams, slides, experiments, and problem statements. Verbal learners prefer spoken or written materials, including questionnaires, tables, texts, lectures, and self-assessments, typically in audio or text formats. Sequential learners prefer materials in linear or hierarchical structures, focusing on procedures, processes, or methodologies with logically ordered steps. Global learners prefer non-linear formats, such as atomic, collection, or networked structures, enabling them to understand the big picture. Suitable resources include overviews, concepts, facts, principles, or summaries for holistic understanding.

The Proposed LORA and Rulesets to Calculate the Ratings

Utilising the associations presented in Table 5, the rule sets have been established to classify whether the LOs are aligned with the associated learning styles. The ruleset is as in Algorithm 1.

Algorithm 1. The Ruleset for Classifying LOs

Dimension: Processing

Rule1: If Learning Style is Active then

Recommended LOM:

(Interactivity type = {Active, Mixed} ∩

Interactivity Level = {Medium, High} ∩

Learning Resource type = {Exercise, Simulation, Questionnaire, Diagram, Figure, Graph, Slide, Exam, Experiment, Problem Statement, Lecture} ∩

Format = {Video, Application, Form})

Rule2: if Learning Style is Reflective then

Recommended LOM:

(Interactivity type = {Expositive, Mixed} ∩

Interactivity Level = {Low, Medium} ∩

Learning Resource Type = {Questionnaire, Diagram, Graph, Index, Slide, Table, Narrative Text, Exam, Self-Assessment, Lecture}" ∩

Format = {Audio, Image, Text})

Dimension: Perception

Rule3: If Learning Style is Sensing then

Recommended LOM:

(Keyword = {Overview, Fact, Procedure, Process, Summary, Assessment} ∩

Format = {Video, Image, Application} ∩

Learning Resource Type = {Simulation, Figure, Graph, Index, Slide, Table, Exam, Experiment})

Rule4: if Learning Style is Intuitive then

Recommended LOM:

(Keyword = {Overview, Concept, Principle, Summary, Assessment} ∩

Format = {Audio, Image, Text} ∩

Learning Resource Type = {Diagram, Narrative Text, Problem Statement, Self-Assessment})

Dimension: Input

Rule5: If Learning Style is Visual then

Recommended LOM:

(Format = {Video, Image, Application} ∩

Learning Resource Type = {Simulation, Diagram, Figure, Graph, Slide, Experiment, Problem Statement})

Rule6: if Learning Style is Verbal then

Recommended LOM:

(Format = {Video, Audio, Text, Application, Form} ∩

Learning Resource Type = {Questionnaire, Index, Table, Narrative Text, Exam, Experiment, Problem Statement, Self-Assessment, Lecture})

Dimension: Understanding

Rule7: If Learning Style is Sequential then

Recommended LOM:

(Structure = {Hierarchical, Linear} ∩

Keyword = {Concept, Procedure, Process, Assessment})

Rule8: if Learning Style is Global then

Recommended LO metadata:

(Structure = {Atomic, Collection, Network} ∩

Keyword = {Overview, Concept, Fact, Principle, Summary, Assessment})

Furthermore, using these rulesets, when a learning object's metadata satisfies a rule, its relevance increases relative to the corresponding learning styles in the learner model. The relevance score is calculated by determining the learning object's weight, reflecting its relevance to the associated learning styles. This is achieved using the formula in Equation 1.

$$\mathrm{LOweight_n} = \sum_{\mathrm{i=1}}^{8} \frac{(Ri\ x\ LSi)}{1100} \tag{1}$$

where,

$LOweight_n$ = the weight of the LO in percentage,
i = ranges from 1 to 8, representing the eight (8) rule sets,
Ri = number of rules satisfied by the LO metadata value space according to the learning styles,
LSi = the probability of learning styles from the learner model,
1100 = represents the maximum score of the LOs

After determining the weight of each learning object, the subsequent step involves implementing the LORA to compute the actual ratings assigned to each learning object. The proposed LORA systematically evaluates LOs based on predefined criteria, ensuring a consistent and objective rating process. LORA is presented in Algorithm 2.

Algorithm 2. LORA

For each $\mathrm{LO_n}$ // The learning object n

1. Score is initialised to 0
2. For each LSi // the learning styles of the students
    a. Count Ri // the number of rules the LO satisfies
    b. Score = Ri * LSi // multiply the number of satisfied rules to the value of learning style
3. totalScore = Score // the total score after looping through all 8 rulesets
4. scorePercent = (totalScore / 1,100) // 1,100 is the maximum points of a learning object
5. finalRating = 1 + (scorePercent * 4) // The Actual Rating of the learning object
6. Display Learning Object Rating Matrix

Following the implementation of the algorithm, the data sparsity of the resulting ratings matrix will be assessed to evaluate the distribution of the rating data. A high level of sparsity may indicate limited user interaction or ratings. The formula used to calculate data sparsity is presented in Equation 2.

$$\mathrm{sparsity} = \frac{N_{observed}}{N_{users}\ *\ N_{items}} \tag{2}$$

where,

$N_{observed}$ = the total number of observed ratings between the students,
N_{users} = the total number of students,
N_{items} = the total number of LOs

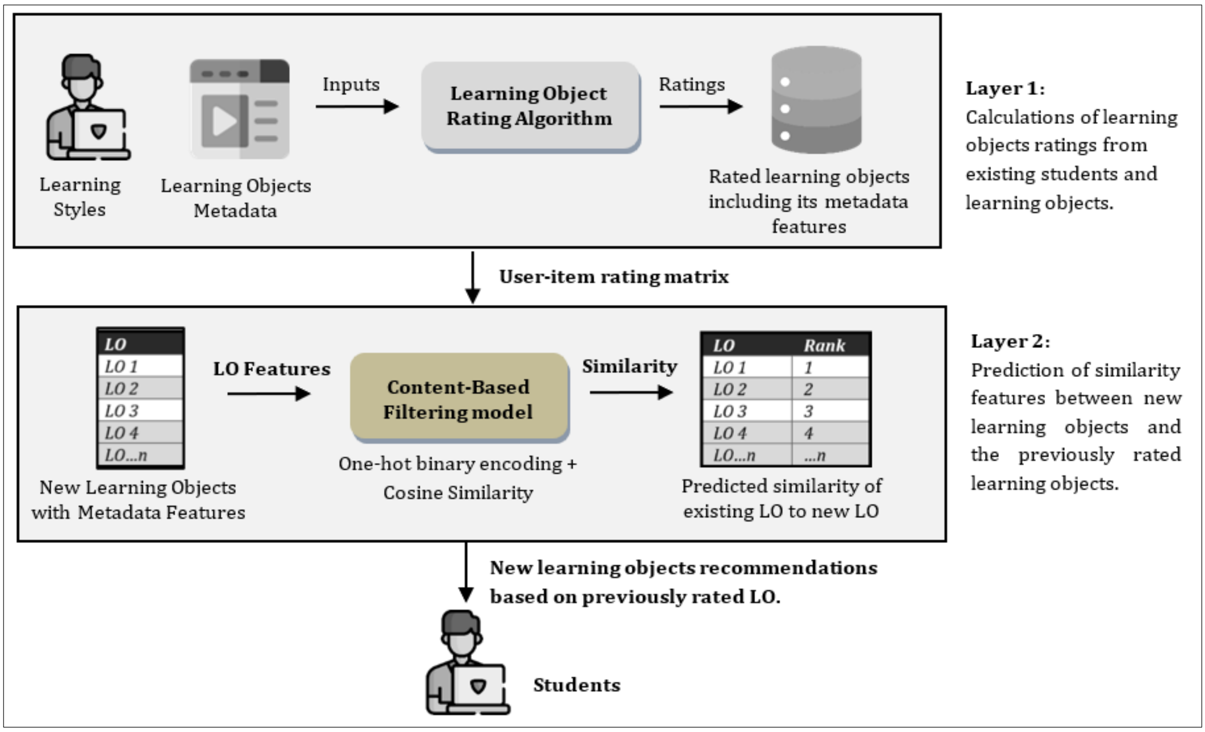
The proposed hybrid learning resource recommender adopts both CBF and CF, using the weighted method for hybridisation. This method adjusts the contribution of CBF and CF based on which algorithm provides better results. Both models were designed independently before being combined into the hybrid recommender.

Predicting Similarities based on the CBF Method

In the CBF model, two layers are involved, as shown in Figure 3. To eliminate the need for prior ratings or interactions, the proposed LORA calculates the probability of ratings between students and LOs using learning styles and metadata as input. The algorithm generates ratings for each learning object, which are then used as input for the CBF model. This also addresses the data sparsity issue by providing ratings for prediction.

Figure 3

The Design Process of the CBF Model with LORA



In the second layer, when new LOs are introduced, the CBF model predicts their similarity to previously rated ones using cosine similarity, as shown in Equation 3. LOs rated by LORA are treated as previously interacted with LOs if no interactions exist. Since the metadata contains nominal values, one-hot binary encoding is used to convert them into numerical vectors.

$$\mathbf{cos}(\boldsymbol{x}, \boldsymbol{i}) = \frac{\boldsymbol{x}.\boldsymbol{i}}{||\boldsymbol{x}|| \ * \ ||\boldsymbol{i}||} \tag{3}$$

where,

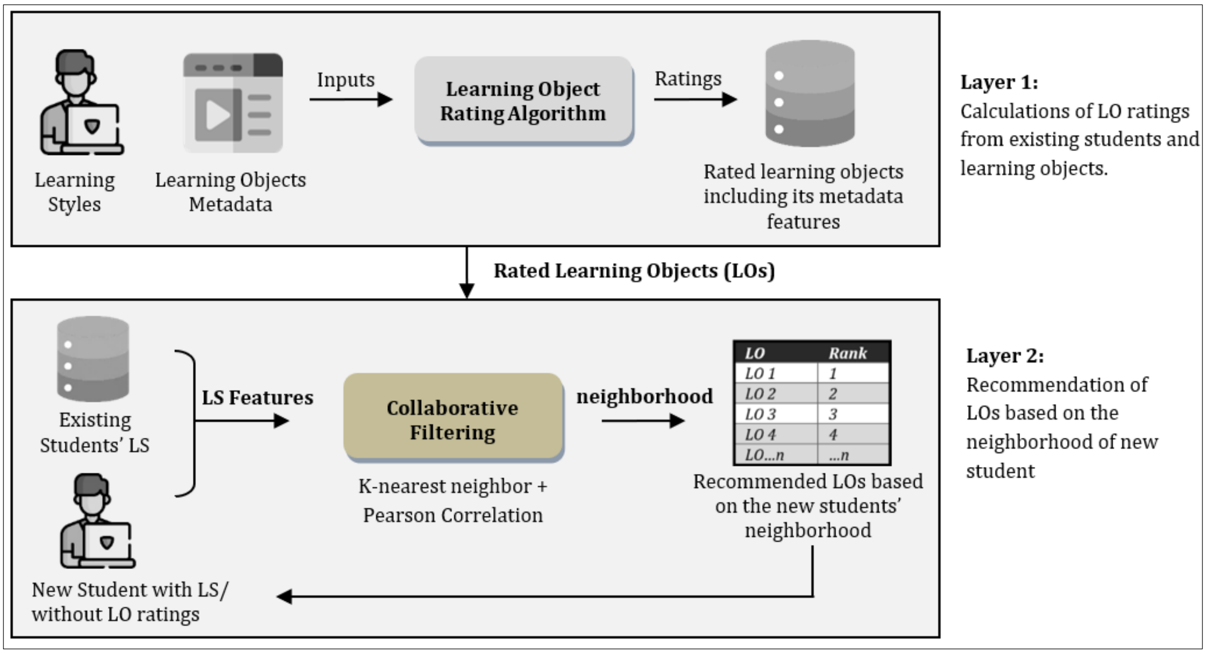
$\boldsymbol{x}.\boldsymbol{i}$ = Measures how much the vector aligns,
$||\boldsymbol{x}|| \ * \ ||\boldsymbol{i}||$ = represents the length of each vector,
$\mathbf{cos}(\boldsymbol{x}, \boldsymbol{i})$ = similarities based on the angle between the two vectors.

Predicting Similarities based on the CF Method

In CF, user-based filtering is adopted. This method does not rely on learning object characteristics but instead uses historical interactions or ratings between students and Los. An approach for the CF model using the LORA is illustrated in Figure 4.

Figure 4

The Design Process of the CF Model with LORA



In this approach, the LORA is implemented in Layer 1 to calculate ratings between LOs and students' learning styles, addressing the data sparsity issue by ensuring sufficient ratings. In Layer 2, the first step is identifying student similarities to form a neighbourhood. The cold-start problem arises when a new student has no prior ratings, but since students are already represented by their learning styles, the method can find similar students and recommend LOs accordingly. Pearson Correlation, shown in Equation 4, is used to identify the K-neighbourhood based on learning style similarities.

$$P(x,y) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\ \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

where,

$\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$ = measures the covariance between $\bar{x}$ and $\bar{y}$, indicating changes in one variable are related to changes in the other,

$\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\ \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ = normalise the covariance by multiplying the standard deviations of $\bar{x}$ and $\bar{y}$, ensuring the result is scale-independent,

$\bar{x}$ and $\bar{y}$ = The mean values of x and y, respectively.

Calculating the Weight of the CBF and CF Models

Lastly, the proposed hybrid learning resource recommender adopts the weighted hybrid modelling method by calculating the alpha value, which determines the weighted contributions of the CBF and CF models for the final recommendation. The alpha value is calculated as shown in Equation 5.

$$P_{hybrid}(u,i) = a * P_{collab}(u,i) + (1-a) * p_{content}(u,i) \quad (5)$$

where,

$P_{hybrid}(u,i)$ = the final prediction for student u and the learning object i
$P_{collab}(u,i)$ = prediction of the CF model for student u and learning object i,
$p_{content}(u,i)$ = prediction of the CBF model for student u and learning object i.
a = weight between 0.0 and 1.0 that balances the contribution of the two recommender models

Moreover, to identify the best alpha value and the final recommender model, prediction accuracy will be measured using Mean Absolute Error (MAE), as shown in Equation 6. The alpha value with the lowest MAE will be selected for the final prediction.

$$MAE = \frac{1}{n}\sum_{i-1}^{n}|yi - \hat{yi}| \quad (6)$$

where,

n = the total number of predictions,
yi = the actual value (ground truth) for the i-th prediction,
$\hat{yi}$ = is the predicted value for the i-th prediction,
$|yi - \hat{yi}|$ = is the absolute error for the i-th prediction

Subsequently, the performance of the hybrid learning resource recommender will be evaluated using precision and recall metrics. The confusion matrix, shown in Table 6, illustrates the tabular representation used to assess model performance (Ibrahim et al., 2020). From this matrix, Precision, Recall, and F-measure are calculated. According to ISO/IEC TS 4213:2022, these metrics offer a comprehensive performance assessment and help identify any model bias or recommendation issues.

Table 6

Confusion Matrix for the Prediction Accuracy

Predicted/Actual	Relevant	Irrelevant
Recommended	True Positive	False Negative
Not Recommended	False Positive	True Negative

$$\textbf{Precision} = \frac{TP}{(TP + FP)} \tag{7}$$

$$\textbf{Recall} = \frac{TP}{(TP + FN)} \tag{8}$$

where,

TP = True Positive, FP = False Positive,
FN = False Negative, TN = True Negative

Furthermore, Precision, as shown in Equation 7, represents the proportion of accurate recommendations among all generated, measuring the system's effectiveness in providing relevant suggestions. Recall, shown in Equation 8, quantifies the percentage of a user's interests successfully identified and recommended, reflecting the system's ability to retrieve relevant items without overlooking important ones (Bhaskaran & Santhi, 2019; Riyahi & Sohrabi, 2020; Venkatesh & Sathyalakshmi, 2020).

RESULTS AND DISCUSSION

Dataset Description

The dataset used in this study includes real-world data comprising the learning styles of 651 students based on the Felder-Silverman Index and 358 LOs for Python and C# programming courses. These LOs were sourced from IEEE LOM Standard-compliant repositories such as MERLOT, ARIADNE, Learn-Alberta, iLumina, and other relevant resources. The course was selected for its foundational concepts, and the Los were modified and validated by faculty experts to ensure alignment with course objectives and university standards. The LORA, implemented in Python, calculated ratings between all 651 students and 358 LOs, generating 217,873 ratings for analysis. To assess data sparsity, Equation 2 was used. With $N_{observed} = 217,874$, $N_{users} = 651$ and $N_{items} = 358$, the data sparsity was approximately 0.065 or 6.52%, indicating a dense dataset. This low sparsity provides more user-item interactions, which in theory can improve the accuracy of the proposed hybrid learning resource recommender model. Table 7 summarises the dataset used for designing and evaluating the model.

Table 7

Summary of the Dataset

Dataset	Total Observed
Learning Styles	651
LOs	358
Rating Matrix	217,873

Hybrid Learning Resource Recommender Model Performance Analysis

Following the processing layer from Figure 2, the CBF and CF models were independently designed and trained using 70% of the dataset. Their performance was evaluated on the remaining 30% test set using MAE, Precision, and Recall metrics, as shown in Equations 6, 7, and 8. The CF model produced an MAE of 0.3168, indicating a relatively low error between predicted and actual ratings. Precision was

0.9495, suggesting 95% of the recommended LOs were relevant, while Recall was 0.8480, showing the model's ability to retrieve a significant portion of relevant items. The CBF model achieved an MAE of 0.2510, indicating an average error of 25.10%. Its Precision was 0.8014, indicating the proportion of relevant recommended objects, and Recall was higher at 0.9730, demonstrating strong effectiveness in retrieving relevant LOs. The evaluation summary is shown in Table 8.

Table 8

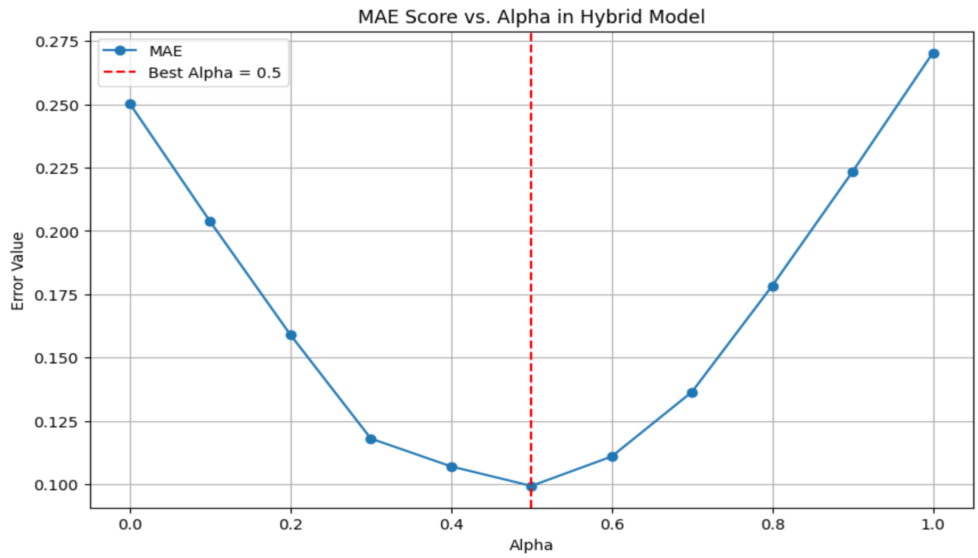
The CBF and CF Model Performance Results

Recommender Model	MAE Score	Precision	Recall
CF Model + LORA	0.3168	0.9495	0.8480
CBF Model + LORA	0.2510	0.8014	0.9730

After designing the collaborative and CBF models, both were integrated to form the hybrid learning resource recommender model. The optimal alpha value was determined through grid search and k-fold cross-validation, evaluating the hybrid model across alpha values from 0.0 to 1.0 using MAE metrics. Each alpha value produced an MAE score, and the one that minimised error and maximised recommendation relevance was selected. Figure 5 shows the alpha values with their corresponding MAE scores. The results indicate that an alpha of 0.5 produced the lowest error, suggesting a balanced combination of collaborative and CBF. This selected alpha was applied in the final hybrid recommender model. Finally, the model was evaluated on the test dataset using MAE, Precision, and Recall.

Figure 5

Result of Grid Search and K-fold Cross Validation Showing the Best Alpha Value



Moreover, Table 9 presents a comparison of the three designed recommender models. The hybrid model achieved an MAE score of 0.1590, indicating a lower error rate than the other models. For Precision, it scored 0.9740, reflecting a high proportion of relevant recommendations. The Recall was 0.9320, showing the model's effectiveness in retrieving a significant portion of relevant LOs. These metrics provide a comprehensive view of the models' performance across different evaluation criteria.

Table 9

Summary of the Recommender Model Performance Results

Recommender Model	MAE Score	Precision	Recall
Hybrid Recommender Model	0.1590	0.9740	0.9320
CF Model + LORA	0.3168	0.9495	0.8480
CBF Model + LORA	0.2510	0.8014	0.9730

Evaluation and Comparative Analysis

This subsection presents a detailed evaluation of the proposed hybrid learning resource recommender model, with a comprehensive comparison to existing hybrid models across multiple dimensions. The evaluation is structured into two aspects: 1) prediction accuracy, measured by MAE, and 2) recommendation effectiveness, measured by Precision and Recall. The results were analysed both statistically and descriptively to understand the model's strengths and weaknesses. Statistical analysis focuses on MAE, Precision, and Recall, quantifying performance and providing numerical insights. Descriptive analysis offers interpretive context, explaining how the hybrid model performs in various scenarios.

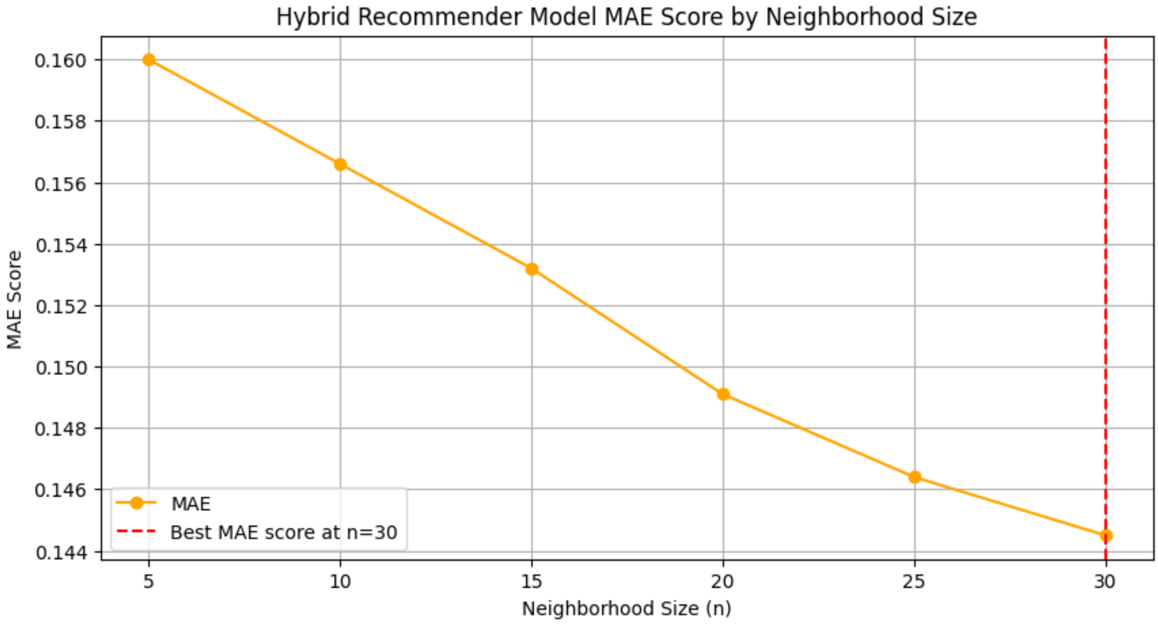
Prediction Accuracy of the Hybrid Learning Resource Recommender Model across Varying Neighbourhood Sizes

The next evaluation analyses the prediction accuracy of the hybrid learning resource model across different neighbourhood sizes, using MAE as the assessment metric. By varying neighbourhood size, the evaluation examines how the number of neighbours influences performance, identifying the optimal size that minimises prediction errors. Neighbourhood size directly impacts the accuracy and quality of recommendations (Jeevamol & Renumol, 2021; Nafea et al., 2019; Riyahi & Sohrabi, 2020; Shu et al., 2018; Wan & Niu, 2020). To determine the best neighbourhood size, the evaluation tested sizes "n" from 5 to 30. A lower MAE indicates higher prediction accuracy.

Figure 6 shows that MAE decreases as neighbourhood size increases, from 0.159 at n=5 to 0.145 at n=30. This suggests the proposed hybrid model performs significantly better in larger neighbourhoods by integrating more user data. With a larger neighbourhood, the model draws on a broader range of similar users, providing a more filtered understanding of preferences and more accurate predictions. The decrease in MAE indicates improved generalisation of user preferences with more neighbours. The results were compared with existing models focusing on MAE at n=5 and n=30. This study's hybrid model, integrating CBF, CF, and LORA, achieved an MAE of 0.159 at n=5, decreasing to 0.145 at n=30. This consistent decrease shows that the model enhances predictive accuracy with more similar users.

Figure 6

Accuracy of the Hybrid Learning Resource Recommender Model across Varying Neighbourhood



In comparison, Table 10 shows Jeevamol and Renumol (2021) who presented a hybrid model combining CBF, CF, and Ontology, with an MAE of 0.79 at n=5, reducing to 0.58 at the optimal neighbourhood size, then slightly increasing to 0.64 at n=30. Shanshan et al. (2021) developed a hybrid model integrating CF, Ontology, and Sequential Pattern Mining (SPM), presenting an MAE of 0.80 at n=5, decreasing to 0.61 at the optimal size, with a minor increase to 0.62 at n=30. Meanwhile, Niyigena and Jiang (2020) combined Ontology, CF, and SPM, generating an MAE score of 0.90 at n=5, 0.80 at optimal size, and 0.83 at n=30. Tarus et al. (2018) designed a hybrid method with Generalised Sequential Pattern Mining (GSP), Context Awareness (CA), and CF, achieving an MAE score of 0.81 at n=5, 0.55 at optimal size, and 0.56 at n=30. The comparison highlights that this study's hybrid model consistently outperforms others across all neighbourhood sizes, with the lowest MAE scores, particularly maintaining 0.145 at the optimal size and n=30. This indicates that integrating CBF, CF, and the LORA provides a more accurate prediction, particularly with larger neighbourhood sizes.

Table 10

Prediction Accuracy Comparisons of Hybrid Recommender Models using MAE across Varying Neighbourhood Sizes

Study	Hybrid Model	n=5	Optimal n	N=30
This Study	(CBF + CF + LORA)	0.159	0.145	0.145
Jeevamol & Renumol, (2021)	(CBF + CF + Ontology)	0.79	0.58	0.64
Shanshan et al. (2021)	(CF + Ontology + SPM)	0.80	0.61	0.62
Niyigena & Jiang, (2020)	(CF + Ontology + SPM)	0.90	0.80	0.83
Tarus et al., (2018)	(GSP + CA + CF)	0.81	0.55	0.56

Precision and Recall of the Hybrid Learning Resource Recommender Model across Different Recommendation Numbers

Furthermore, the next evaluation assesses the effectiveness of the hybrid learning resource recommender model in recommending relevant LOs, using Precision and Recall as key metrics. Precision measures the proportion of recommended LOs that are relevant, while Recall evaluates the model's ability to identify all relevant items in the dataset. A rating of 3.0 and above was used to determine relevance; recommendations scoring at or above this threshold are considered relevant, while those below 3.0 are irrelevant (Jeevamol & Renumol, 2021; Tarus et al., 2018; Wan & Niu, 2020; Xiao et al., 2018). The evaluation was conducted across varying numbers of recommendations, from 5 to 30, to analyse how the model's effectiveness changes as the recommendation list expands. This approach allows for detailed insights into its performance in recommending relevant LOs.

The analysis revealed a significant trade-off between Precision and Recall, as shown in Figures 7 and 8, respectively. At recommendations=5, the model achieved a high Precision of 0.932, meaning 93% of the top 5 recommended LOs were relevant. However, Recall was low at 0.152, indicating only a small portion of all relevant items were captured. As the number of recommendations increased to 10, Precision remained high at 0.922, while Recall rose to 0.297. This trend continued at recommendations=15 and 20, where Precision slightly dropped to 0.915, but Recall increased to 0.590 at 20. At recommendations=25 and 30, Precision declined further to 0.901 and 0.881, respectively, showing a reduced proportion of relevant items among recommendations. However, Recall improved to 0.727 at 25 and 0.853 at 30, indicating the model's growing ability to retrieve more relevant Los with a longer recommendation list.

Figure 7

Precision of the Hybrid Learning Resource Recommender Model

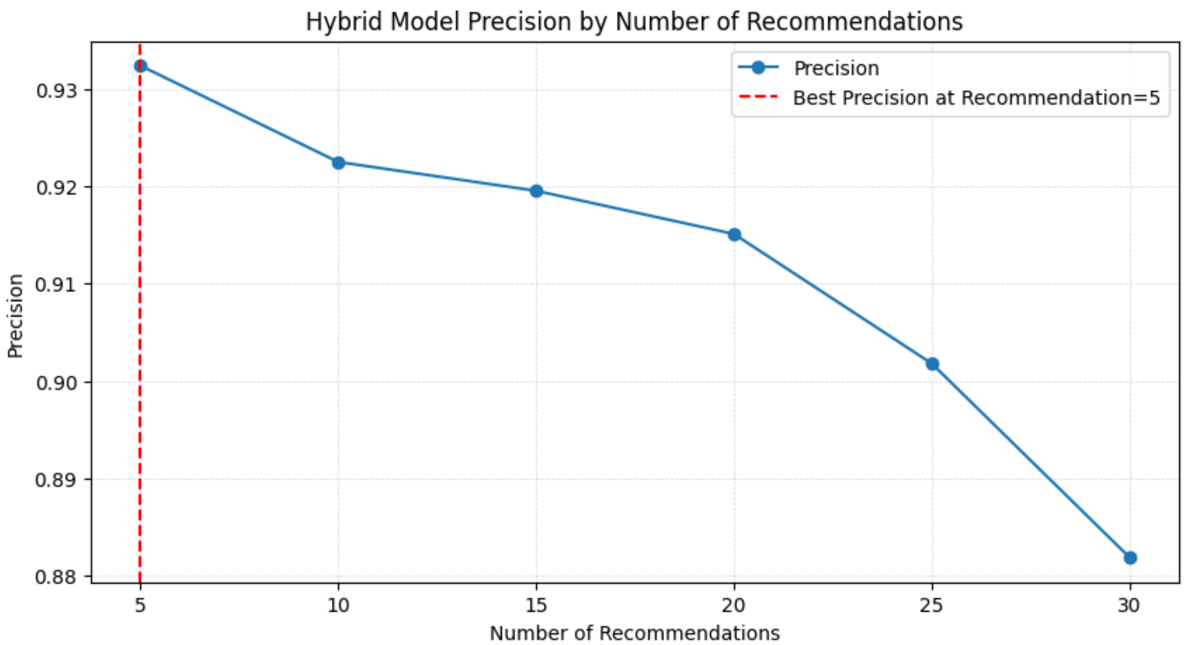
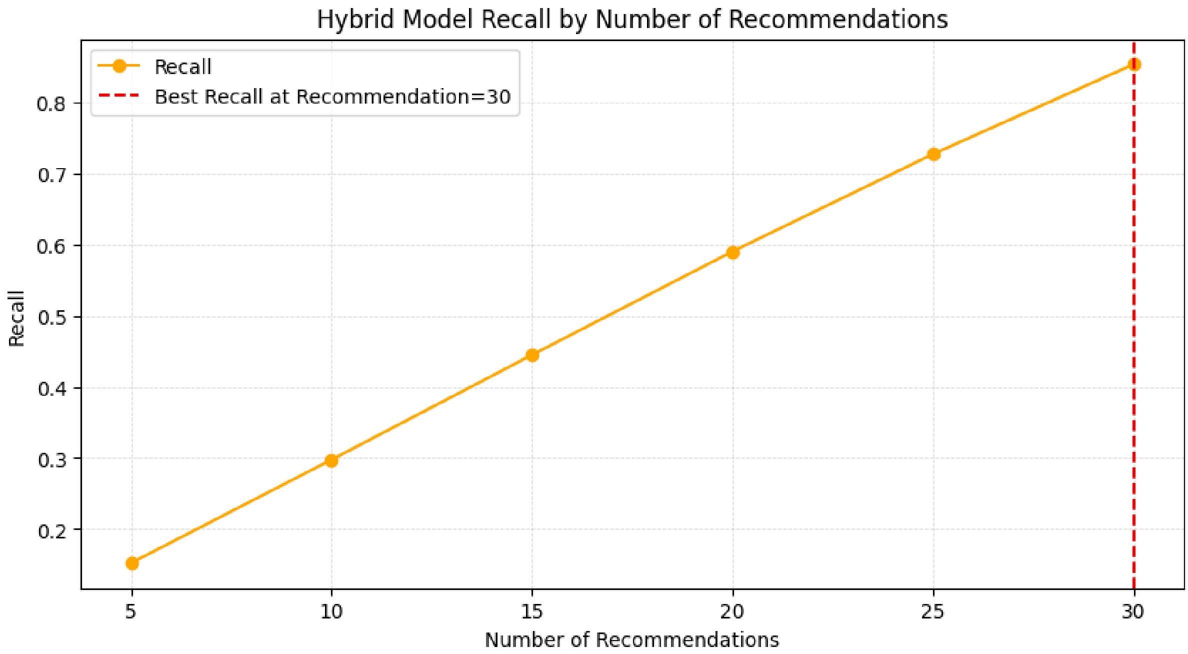


Figure 8

Recall of the Hybrid Learning Resource Recommender Model



These results highlight a negative correlation between Precision and Recall in the hybrid learning resource recommender model. A smaller number of recommendations tends to yield higher Precision, while expanding the list improves Recall, often at the cost of Precision. In this study, the relevance of recommended LOs is emphasised, making Recall important as it reflects alignment with students' learning styles (Jeevamol & Renumol, 2021; Nafea et al., 2019; Shu et al., 2018). However, while higher Recall ensures more relevant objects are included, it can reduce Precision, leading to more recommendations that may not fully match student preferences. Focusing on Precision helps ensure recommendations are better aligned with learning styles. Based on the results, the hybrid model is set to recommend 30 items, as this provides a balance between good Precision and Recall.

Moreover, Table 11 presents a comparative analysis of Precision and Recall across various studies implementing hybrid recommender models, focusing on accuracy and number of recommendations. The hybrid model in this study achieved a Precision of 0.881 (88.1%) and a Recall of 0.853 (85.3%), indicating high relevance and strong ability to identify relevant LOs. In contrast, Jeevamol and Renumol (2021) presented a Precision of 0.750 and a Recall of 0.730, showing broader coverage with slightly reduced accuracy. Shanshan et al. (2021) achieved a Precision of 0.670 and a Recall of 0.720, reflecting moderate accuracy and high coverage. Niyigena and Jiang (2020) presented a hybrid model with a Precision of 0.571 and a Recall of 0.541, showing balanced but lower overall performance. Tarus et al. (2018) presented a Precision and Recall of 0.481 and 0.451, respectively, indicating less accurate and comprehensive recommendations compared to the other models.

Table 11

Prediction Accuracy Comparison of the Hybrid Learning Resource Recommender Model across Varying Neighbourhood Sizes

Study	Hybrid Model	n=5	Optimal n	R
This Study	CBF + CF + LORA	0.881	0.853	
Jeevamol and Renumol (2021)	CBF + CF + Ontology	0.750	0.730	
Shanshan et al. (2021)	CF + Ontology + SPM	0.670	0.720	r>=3.0
Niyigena and Jiang (2020)	CF + Ontology + SPM	0.571	0.541	
Tarus et al. (2018)	GSP + CA + CF	0.81	0.55	

When comparing the performance results, it is revealed that this model prioritises the balance of Precision and Recall, achieving scores of 0.881 and 0.853, respectively. This indicates that the model's recommendations are more accurate and better aligned with users' preferences. In contrast, other studies show lower Precision but higher Recall, reflecting broader yet less precise coverage. The higher Precision in this model can be attributed to its integration of CBF, CF, and the LORA, which emphasises recommending highly relevant LOs. This focus on relevance contributes to its strong Precision performance, ensuring recommendations meet learners' needs and preferences. Based on these results, the study reduces irrelevant suggestions while maintaining a balance of relevant items, avoiding overwhelming students with less aligned options.

CONCLUSIONS AND FUTURE WORKS

This study conducted a comprehensive investigation into existing problem statements to establish a theoretical foundation for designing the proposed hybrid learning resource recommender model, with particular focus on addressing the data sparsity problem. It examined several key areas relevant to this research, including understanding learning styles and designing the learner model using the Felder-Silverman Learning Style Model, describing learning resource characteristics using the IEEE LOM Standard, and designing the LORA. The LORA played a significant role in enabling the proposed model to generate predictions by calculating ratings between learners and LOs, thereby helping to mitigate the data sparsity problem. The overall contributions of this research are as follows:

1. The integration of learning styles and learning object characteristics has been identified as an important component of the proposed hybrid learning resource recommender model.
2. The mapping between learning styles and LOs enables the LORA to mitigate the data sparsity problem in the user-item rating matrix, thereby allowing the proposed hybrid learning resource recommender model to make accurate predictions.
3. Using an algorithm to calculate ratings instead of over-reliance on user-provided ratings has been explored as a solution to improve recommendation accuracy and reduce data sparsity.

Future studies may consider enhancing LORA by integrating additional student characteristics beyond learning styles, such as personality traits, individual interests, or academic performance of students, through the implementation of the recommender system using a quasi-experimental design or similar methodologies. This would allow for a more comprehensive evaluation of how these factors influence the effectiveness and accuracy of the hybrid learning resource recommender model. In addition, it is important to test the proposed model in real classroom environments by integrating it into a Learning Management System (LMS), enabling the assessment of its performance in authentic educational settings. Furthermore, learner satisfaction remains a crucial aspect of recommender systems that require deeper investigation, as understanding how students perceive and engage with the recommended resources can provide valuable insights for refining the model.

Overall, this study contributes to ongoing research on adaptive learning and educational recommender systems by designing a structured approach to personalising learning resource recommendations. It presents a systematic method for aligning resources with individual learner characteristics through the combination of learning styles, structured metadata, the LORA, and hybrid recommendation techniques. The research establishes a framework for designing a recommender model that addresses key challenges such as data sparsity, personalisation, and adaptability. The proposed approach outlines a procedure for modelling the learner and selecting relevant LOs based on quantifiable attributes, while allowing for adjustments in various educational contexts.

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