A Context-Aware Hybrid Recommendation Framework for E-Learning Platforms

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***Abstract*—E-learning platforms provide learners with extensive digital resources that enable self-paced and location-independent study. However, the overwhelming volume of learning materials offered by a wide range of institutions and content providers makes personalized guidance increasingly essential for effective knowledge acquisition. As a result, recommender systems have become fundamental components of modern e-learning environments, helping to reduce information overload and support individualized learning experiences. In general, the richer and more diverse the available data, the more accurate and relevant the resulting recommendations. Despite these advantages, conventional recommendation approaches often fail to fully exploit the contextual and relational information inherent in e-learning ecosystems, which limits their adaptability and predictive precision. This study proposes a hybrid recommendation framework that integrates collaborative filtering, content-based filtering, and context-aware modeling to generate more accurate and adaptive course recommendations. The proposed system infers learner preferences by combining historical interaction data, contextual attributes, and course characteristics, while also incorporating temporal and environmental factors that influence learning behavior. Experimental evaluations based on SVD, TF-IDF, and RNN models applied to a well-established benchmark dataset demonstrate that the proposed hybrid framework significantly improves recommendation accuracy, coverage, and adaptability compared with baseline methods. Furthermore, the integration of contextual information effectively alleviates the cold-start problem and better captures learners' evolving goals and learning trajectories. Overall, the results confirm that combining multiple recommendation paradigms within e-learning platforms enables more adaptive, personalized, and scalable learning pathways, making the proposed system suitable for diverse educational contexts and learner profiles.**

Keywords*—E-learning; recommender systems; hybrid approach; personalized learning; course

I. Introduction

The flexibility of e-learning systems has fundamentally transformed the way students learn and how education is delivered. These platforms enable self-directed and personalized learning experiences, allowing learners to acquire new skills and knowledge beyond the traditional classroom. The COVID-19 pandemic further highlighted the critical role of e-learning technologies, as they were rapidly adopted to ensure educational continuity during periods of disruption. However, modern e-learning platforms offer an enormous number of courses and digital learning resources [1]. This abundance often leads to information overload, making it difficult for learners to identify and select content that aligns with their academic objectives, learning styles, and personal preferences.

In this context, recommender systems (RSs) play a crucial role in helping learners discover relevant educational resources from large collections of courses [2][3]. In domains such as e-commerce, entertainment, and social media, recommender systems based on Collaborative Filtering (CF) and Content-Based Filtering (CBF) have demonstrated strong performance. CF predicts user interests by identifying similarities among users and items using interaction histories such as ratings, clicks, and browsing behavior [4], [5]. In contrast, CBF recommends items by analyzing content features, including course descriptions, topics, and keywords, and matching them to a user's previous preferences [6], [7]. This approach relies on comparing new items with those previously consumed to determine suitable recommendations.

Despite their success, these techniques exhibit important limitations when applied to e-learning environments. CF suffers from the cold-start problem and data sparsity, particularly when new users or new courses have limited interaction history [8], [9]. CBF, on the other hand, relies on static content representations and therefore struggles to adapt to learners' evolving goals and situational learning contexts [10].

To overcome these limitations, recent research has focused on hybrid recommender systems that combine multiple recommendation strategies to exploit their complementary strengths. Several studies [11], [12] have shown that incorporating additional information especially contextual data—significantly enhances recommendation performance. In e-learning environments, contextual factors such as the device used, time of access, location, and session duration strongly influence learners' behavior and course preferences. For example, a learner accessing the platform from a mobile device may prefer short tutorials, whereas the same learner using a desktop computer at home may be more inclined to engage in longer and more comprehensive learning modules [13].

The present work proposes a hybrid e-learning recommender system that integrates Collaborative Filtering, Content-Based Filtering, and contextual modeling to provide personalized and context-aware course recommendations. Contextual information is modeled using predictive LSTM neural networks to capture temporal and behavioral patterns, while SVD is employed for matrix factorization and TF-IDF for textual feature extraction and natural language processing.

This study makes several important contributions. First, it introduces a hybrid recommendation framework that jointly leverages collaborative, content-based, and contextual modeling techniques to enhance personalization in e-learning environments. Second, it integrates SVD, TF-IDF, and LSTM to address key challenges such as data sparsity, cold-start issues, and evolving learner behavior. Third, the framework is extensively evaluated using real edX course data, demonstrating superior performance over traditional CF and CBF methods in terms of accuracy, relevance, and contextual adaptability.

The remainder of this study is organized as follows: Section II reviews related work on hybrid recommender systems and discusses the limitations of existing approaches. Section III presents the proposed framework and methodology. Section IV describes the experimental setup, including evaluation metrics and results. Finally, Section V concludes the study and outlines directions for future research.

II. Related Work

With the use of recommender systems, user experiences across many areas, including e-learning, have been personalized to individual user needs [14], [15]. These systems suggest activities based on users' previous activities [16], [17]. The first recommender systems relied on Collaborative Filtering (CF) and Content-Based Filtering (CBF). CF analyzes user-item interactions based on attribution, clicks, and behavior to find patterns of similarity among users or items [17]. CF is effective in many scenarios, but sparse data, new users, and the absence of interaction data (cold-start) is highly problematic. Other techniques, such as predictive analytics, have been proposed to solve these issues, but CF continues to have difficulty adapting to changing environments and user preferences.

CBF improves on CF by using items features (keywords, topics, and metadata). In e-learning, CBF analyzes course materials to recommend resources that adjust to learner preferences based on their previous activities [15]. CBF's major problem is its over-specialization. It limits user exploration by not encouraging them to search outside the narrowly defined parameters of their needs [14]. Additionally, its use of static features fails to capture the user's evolving needs [16], [18].

Hybrid recommender systems integrate the strengths of Collaborative Filtering (CF) and Content Based Filtering (CBF) techniques to provide the users of e-learning platforms engaged and more targeted suggestions [19]. The addition of deep learning methods, such as neural collaborative filtering, which provides the ability to work on and analyse intricate relationships and non-linear user-item interactions, is a recent and notable advancement in this area [20].

Although hybrid systems have progressed in many ways, they still have a critical oversight of failing to integrate contextual data which includes how, when, and where a user interacts with the learning materials [21][22]. CARS approaches this oversight with contextual data such as study times, types of devices, locations, and other time constraints for learning materials [18]. For instance, recommending longer courses for uninterrupted study times and shorter tutorials for commuting is likely to improve learning and the perceived value of the recommendations. Including context data in recommendations has been shown to improve accuracy and user satisfaction [19].

Nonetheless, many CARS approaches for context modeling remain rudimentary or involve only fragmentary contextual details, leading to unfulfilled personalization. Moreover, context modeling intricacy might lead to scalability issues and pose problems for real-time adaptation which, in turn, limits responsiveness in swiftly evolving learning settings, as noted in [23]. This is why CF, CBF, hybrid and context-aware models still default most of the time in handling the interplay of collaborative, content, and contextual pieces. In addition, they tend to be responsive inflexibly to learner's situational alterations, state of cold start, and real-time adjustments of behavior or situational aspects of the environment [22].

In light of these challenges, this research aims to develop a hybrid e-learning recommender system that combines elements of collaboration, content, and contextual strategies within a single framework. This system develops sophisticated SVD models for matrix factorization, employs TF-IDF for feature embedding, and uses RNNs for sequential behavior modeling. By dealing with user-specific preferences and shifting contextual factors, the integrated approach improves the precision, diversity, and contextual relevance of recommendations. On a wider frontier, this fully personalized system addresses scalability and adaptive challenges while providing personalization within the learning pathways for a diverse learner's spectrum and within a robust and dynamic real-world e-learning context, as detailed in [21, 24].

Proposed system considers the issues in previous works and focuses on providing an adaptive solution that offers flexibility and overcomes the many restrictions traditional e-learning recommender systems face. For instance, cold-start, data sparsity, overspecialization, and an adaptive approach towards changing user preferences are stick points for Collaborative Filtering (CF) and Content-Based Filtering (CBF) systems. Although hybrid approaches try to associate CF and CBF, many fail to consider the user context while learner interactions and user preferences are adjusted. The proposed system overcomes this shortcoming by providing context-aware integration of-collaborative, content, and CBF approaches. Thus, achieving a comprehensive, synergistic recommendation framework.

One of the strengths of this system is the management of user behavior over time. User behavior on e-learning platforms is not fixed; it changes as users learn new topics, reorganize their study plans, or adapt to other external factors like the availability of devices and location. Fleeting and situational conditions allow the system to revise recommendations in real time, attuned to the user's present needs, offering resources that are relevant and actionable. The ability to track changes user behavior over time and in real time is a significant improvement over traditional CF and CBF, which tend to provide users with recommendations that are the same over extended periods and are based on stale historical behavior patterns or unchanging attributes of the content.

In addition, system parameters that analyze the user's context, including limitations and learning goals, are vital to personalization in e-learning. Session length, time of access, and device type are examples of context variables that help to adapt recommendations to user learning environments. In addition, learning goals help the system to prioritize targets aligned with users–whether for skill building, exams, or professional learning. Context and goal alignment together ensure that the system moves beyond offering vague, unhelpful recommendations to the user and supports actionable recommendations.

Overall, the proposed hybrid system is a significant improvement over the previous work which is focused on e-learning recommendation systems. It closes the gaps between the collaborative, content-based, and context-approaches, facilitating the generation of adaptive, flexible, and personalized learning paths. This not only contributes to higher recommendation accuracy and user satisfaction, but also to the advancement of intelligent context-aware e-learning systems aimed at meeting the needs of a variety of learners in real-life educational environments.

Recent research in e-learning recommendation systems has shown a clear trend toward hybrid and context-aware approaches, which combine multiple techniques to improve personalization and system adaptability in response to the diversity of learners and learning contexts. For instance, hybrid approaches integrating user and content-based techniques with collaborative methods have been proposed to address the cold-start problem in personalized course recommendation systems, demonstrating increased user satisfaction without relying solely on historical user ratings [25]. Similarly, context-aware recommendation engines integrating hybrid reinforcement learning have been developed to dynamically adapt recommended content according to learner profiles, preferences, and real-time performance, illustrating the integration of various contextual data such as learning pace and individual trajectories [26]. Moreover, systematic reviews of recent advances in context-aware recommender systems highlight the importance of structured contextual representations and integrated methods to capture complex interactions among users, items, and context, while emphasizing the need for more unified frameworks for context management [27] [28]. Other studies explore group or multi-criteria recommendation mechanisms, showing the addition of diverse contextual factors and dynamic attention mechanisms to better serve collaborative or multi-dimensional educational environments [29] [30]. Federated hybrid approaches have also been proposed to address challenges related to inter-institutional diversity and data privacy, constructing heterogeneous representations that integrate historical and contextual interactions within distributed learning graphs [27] [28]. Finally, research on hybrid and context-aware recommendations in adjacent domains demonstrate the positive impact of combining multiple paradigms on recommendation accuracy and adaptability, providing a solid conceptual foundation for hybrid context-aware frameworks in e-learning [31].

III. Proposed Framework and Methodology

We aim to enhance personalization and flexibility in e-learning recommendations by designing a hybrid recommendation framework that integrates Collaborative Filtering (CF), Content-Based Filtering (CBF), and Contextual Data Modeling (CDM) using Long Short-Term Memory (LSTM) networks. By combining these three approaches, the framework overcomes the limitations of relying on a single recommendation technique and enables more accurate, diverse, and context-aware learning recommendations.

Collaborative Filtering (CF) identifies users and groups with similar preference patterns, behaviors, and interaction histories. It analyzes user–item interaction matrices and recommends courses that have been highly rated or frequently accessed by users with similar profiles. However, CF suffers from data sparsity and cold-start problems, particularly when dealing with new users or newly introduced courses.

Content-Based Filtering (CBF) relies on course attributes such as keywords, topics, descriptions, and metadata to match learning resources with individual learner profiles. This approach is effective in recommending courses aligned with a learner's past interests and completed materials. Nevertheless, CBF often leads to over-specialization, as it tends to recommend content that is too similar to previous selections, thereby limiting exploration and discovery of new topics.

Contextual Data Models capture situational factors that influence learning behavior, including temporal variables (e.g., study schedules and session duration) and spatial or environmental attributes such as location, device type, and learning context. To model these complex and sequential relationships, we employ Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks capable of learning long-term dependencies in user behavior. Through LSTM, the system analyzes how learners' preferences and contexts evolve over time and predicts which courses are most suitable at a given moment. For instance, the system may recommend short tutorials during commuting or brief study sessions, while suggesting more comprehensive modules during extended learning periods.

Each component—CF, CBF, and the LSTM-based contextual model—operates independently to generate candidate recommendations. These outputs are then combined through a fusion mechanism that considers user reliability, behavioral profiles, and contextual relevance. This hybrid aggregation strategy provides dynamic recommendation capabilities, allowing the system to adapt to changes in learner preferences and environmental conditions in real time.

By integrating collaborative, content-based, and contextual modeling approaches, the proposed framework offers a flexible, scalable, and context-sensitive solution for e-learning personalization. It simultaneously exploits historical interaction patterns, course attributes, and situational factors to deliver highly relevant and adaptive recommendations, ultimately enhancing learner engagement, effectiveness, and satisfaction.

A. Framework Overview

Fig. 1 will help to explain the elements of the blended recommendation framework. There are four blended recommendation framework parts that are unified, which help to generate hyper-personalized course recommendations. The modular approach also allows the recommendation system to gain different facets of a learner's behavior, a course's content, and contexts, leading to comprehensive recommendations. Since diverse aspects of learner behavior and content are accounted for, the recommendations are comprehensive and accurate.

1) Collaborative Filtering (CF) with SVD (User-Based Collaborative Filtering – UBCF): The first segment uses the previously discussed user-item historical interaction data of ratings, clicks, or engagement trails to locate and analyze user similarities. SVD (Singular Value Decomposition) transforms the user-item interaction matrix by decomposing it into a set of latent factors that the system can use to uncover hidden user preferences and help outline custom course recommendations by analyzing the adjusted suggestions of comparable users. The UBCF (User-Based Collaborative Filtering) approach, which focuses on learners with comparable profiles, also improves the relevance of recommendations. Latent factor modeling UBCF also solves some of the sparsity issues.

2) Content-Based Filtering (CBF) with TF-IDF: The second module analyzes each course and matches it with user profiles. Using TF-IDF (Term Frequency-Inverse Document Frequency) algorithm, the system analyzes course descriptions, keywords and other textual features and metadata, and assesses the relevance of each course in relation to the learner's prior choices. This component guarantees that the recommendations correspond to the learner's interests and areas of knowledge. In contrast to CF, CBF can algorithmically recommend new courses, thus alleviating cold-start challenges for new items.

3) Contextual modeling with LSTM networks: Incorporating the third constituent, the bloc incorporates contextual information that makes it possible to understand the temporal and situational aspects of user behavior. Using Recurrent Neural Networks (RNNs) with Long Short Term Memory (LSTM) units, it tracks the sequence of data in learner interactions and analyzes the timestamps, devices, and contexts of each session. LSTM networks are designed to remember information for long periods which allows the system to change recommendations as user behavior and preferences shift, enabling situational personalization. For example, it can offer short tutorials when users are likely to be commuting and more comprehensive modules are reserved for heavier study sessions which increases relevance and engagement.

4) Hybrid aggregation mechanism: This last building block combines the results from CF, CBF, and the LSTM-based contextual model. Based on the relevance, reliability, and contextual appropriateness of each module, the recommendations are weighted and aggregated into a comprehensive, context-aware recommendation list. This fusion mechanism maintains equilibrium in the hybrid system while interlocking each model's pivots. Whereas CF focuses on the community trends, CBF captures the content relevance, and the LSTM-based CDM integrates the situational and temporal aspects.

Collectively, these four components provide a powerful, flexible, and expandable framework capable of offering highly personalized e-learning recommendations. In addition to enhancing prediction accuracy, the architecture improves learner satisfaction and engagement by resolving challenges associated traditional models, such as the cold-start problem, static content dependence, and the absence of contextualization.

B. Framework Development Process

Constructing the hybrid framework is based on an organized multi-step pipeline where all parts are built on the edX Course Data dataset.

1) Data preprocessing: The information in the dataset falls into three categories: i) the history of user interactions with items, including clicks, ratings, enrollments, and course completions; ii) course metadata which encompasses description, categories and keywords, as well as information about the instructor; iii) contextual data which includes timestamps, device types, and session information. The cleaning process for this phase involves removing outliers and handling missing values, which requires the use of either imputation or removal techniques. Categorical variables such as user demographics and course categories are encoded through one-hot or label encoding, while numerical features such as ratings and time spent are normalized to a consistent scale.

Moreover, feature engineering refines user interactions to create the user-item interaction matrix for collaborative filtering (CF). For content-based filtering (CBF), course metadata is used to extract TF-IDF features. Additionally, time-series structured contextual data is prepared for training the RNN-based models.

2) Independent model implementations:

- Collaborative Filtering using SVD: The interaction matrix is split into latent factors for users and courses. Ratings for non-evaluated items are predicted using the dot product of these vectors, enabling user-specific recommendations to be tailored.
- Content-Based Filtering using TF-IDF: For textual features of the courses, TF-IDF scores are calculated. Using cosine similarity, a user's preference profile is measured against course content to rank and recommend the most relevant ones, thus enabling course ranking and recommendation.
- Contextual Model using RNN: Sequences of user behaviors along with contextual variables like device used and time are formatted as ordered sequences and used to train the RNN. The RNN LSTM captures temporal regularities and makes predictions for user preference scoring to recommend relevant courses.

3) Score normalization: Each model's CF, CBF, and RNN outputs are normalized to the [0, 1] range using Min-Max Scaling. This normalization guarantees model output comparability and is crucial for effective aggregation.

Before fusion, the outcomes generated by each model, specifically the Collaborative Filtering, Content-Based Filtering, and the Recurrent Neural Network, are scaled down to the $[0, 1]$ interval using the Min-Max scaling method. This step is crucial since the models feature scores that differ in terms of numerical consistency, distribution, and in the case of CBF, may even utilize a distinct calculating method. Model outputs entail dissimilar Merits, valued predictions, range estimates, or probabilities. Without the Min-Max scaling, the more significant the range of a score, the more influence it would have on the fusion process leading to skewed and unreliable recommendations.

In relation to a specific predictive score s_i, that a model outputs for a single learner x item combination, the Min-Max normalization is described as follows:

$$s_i^{\text{norm}} = \frac{s_i - s_{\min}}{s_{\max} - s_{\min}}$$

where, $s_{\min}$ and $s_{\max}$ denote the minimum and maximum scores generated by the model for a given learner–item pair,

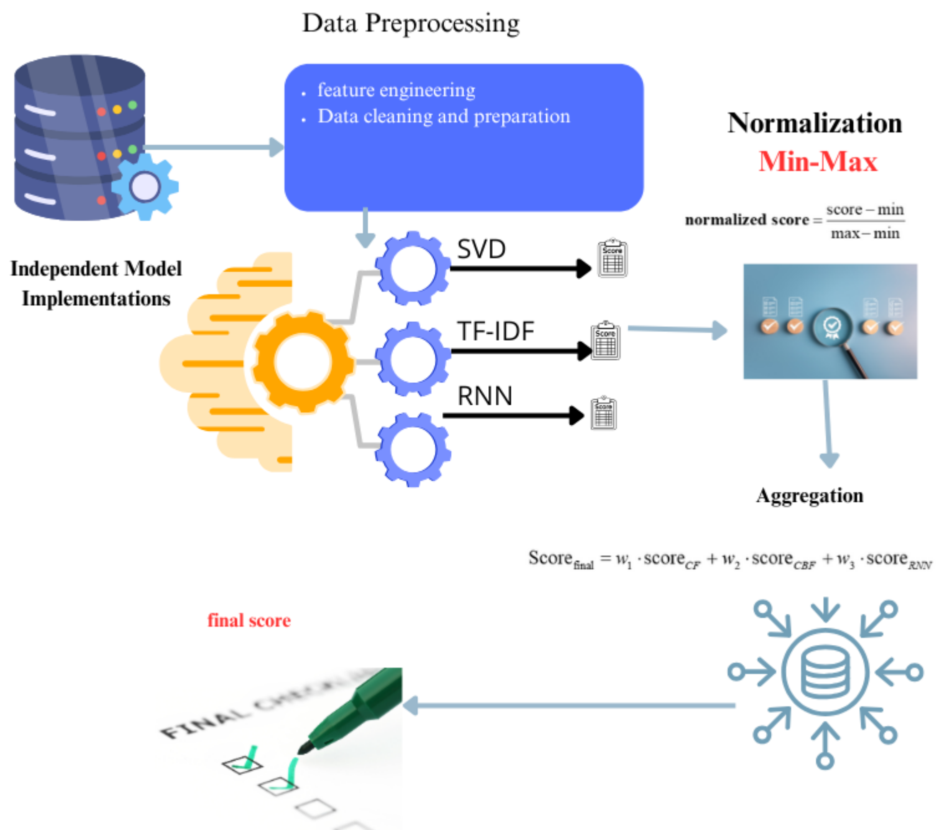

Fig. 1. Framework overview.

respectively, thereby rescaling all outputs to a common range between 0 and 1.

With the normalization process, the same score level is bestowed upon each model, proving a fair ground for comparison, and in-turn a more precise aggregation technique is applied to the weighted fusion layer. This directly increases the quality of each component in the score fusion process and adds more to the system as a whole in terms of reliability, consistency, and more comprehensibility to the hybrid recommender system.

4) Result aggregation: The normalized outputs of the three recommendation models namely the SVD-based collaborative filtering module, the TF–IDF content-based module, and the RNN-based contextual module—are combined using a weighted hybrid aggregation strategy. Each model is assigned a weight according to its predictive performance on the validation set, such that models achieving higher accuracy (i.e., lower prediction error) contribute more to the final recommendation; the corresponding computed weight values are reported in Table I.

Let E_i denote the prediction error of model i, measured using RMSE or MAE. The adaptive weight w_i associated with each model is computed as the normalized inverse of its error:

$$w_i = \frac{\frac{1}{E_i}}{\sum_{j=1}^{3} \frac{1}{E_j}} \quad (1)$$

This formulation ensures that models with lower prediction errors receive higher weights, thereby exerting greater influence on the final recommendation score. For instance, if the RNN model achieves the lowest RMSE among the three, it is assigned the largest weight, followed by the TF–IDF and SVD models.

Let $S_i(u, k)$ represent the normalized score produced by model i for user u and course k. The final hybrid recommendation score is then computed as:

$$\begin{aligned} S(u,k) = {} & w_{\text{SVD}}\, S_{\text{SVD}}(u,k) \\ & + w_{\text{TF-IDF}}\, S_{\text{TF-IDF}}(u,k) \\ & + w_{\text{RNN}}\, S_{\text{RNN}}(u,k) \end{aligned} \quad (2)$$

This adaptive fusion mechanism enables the recommender system to dynamically balance collaborative, content-based, and contextual signals according to their reliability under the current data conditions. As a result, the hybrid model achieves greater robustness and predictive accuracy than any individual component, while remaining responsive to variations in learner behavior and contextual factors.

5) Evaluation: Evaluate the performance of the individual models and the hybrid system using the following metrics: Precision@K: Measures the proportion of relevant items in the top-K recommendations, and the Recall@K: Assesses the fraction of relevant items retrieved out of all applicable items,

TABLE I. ADAPTIVE WEIGHTING OF SVD, TF–IDF, AND RNN MODULES BASED ON RMSE.

Module	RMSE	Weight w_i
SVD	0.902	0.30
TF–IDF	0.856	0.32
RNN	0.812	0.38

Normalized Discounted Cumulative Gain (NDCG): Takes into account the rank position of recommendations, giving higher importance to higher-ranked items,Root Mean Squared Error (RMSE): Evaluates the accuracy of the predicted ratings, comparing the difference between predicted and actual values. Algorithm 1 and Algorithm 2 presents the hybrid recommendation systems.

IV. RESULTS AND DISCUSSION

This section describes how we evaluated hybrid e-learning recommender systems using the rich edX Course Data. As data collected from millions of learners around the globe, it incorporates different views to analyze learner disposition. As we developed and tested advanced recommendation systems, the data also allows us to understand learner behavior, course content and the context within which the recommendations were made.

The dataset consists of three major parts. The first part containing data of user interactions records course enrollments and completions, audit, ratings, and detailed activity logs. Every interaction captures unique and important behavioral components of learners thus helping to model long-term interest and short-term engagement. Such user behavior data allows the recommender system to not only find and cluster learners with similar and competing interests but also track the dynamic order and sequence of courses to predict the next course a learner might be interested in.

The course metadata contains both structured and unstructured texts, for example, course titles, descriptions, types, keywords, and other content descriptors. This information is essential for the content-based filtering component, as it allows cross matriculation of learner profiles and courses with pertinent characteristics. The richly developed text features provide enough information for the model to capture the semantics of various courses, allowing it to recommend those that best align with what the learner has engaged with or indicates interest in.

A. Dataset

The datasets used in this research study are collected from edX, a popular resource for academic research in e-learning and educational recommendation systems. The dataset includes a total of five thousand learners, one thousand learning resources, and five thousand unique user-to-resource interactions, indicating a collection of diverse learning behaviors and content engagement patterns.

User-resource interactions can be classified to indicate whether a learner has performed an action with a particular educational resource. Actions may include registering for a course, browsing content, watching videos, or submitting assignments. These action behaviors are used as signals within the collaborative filtering component to learn user preferences, while the TF–IDF descriptive and textual resource data learn user content preferences. Additionally, the data collected over time helps the RNN capture and model the time dimensions of learning behaviors to address the shift in learners' interests and learning paths.

A standard hold-out protocol was used to split the dataset into two non-overlapping subsets for model training and evaluation: 80% of the dataset was allocated for training, while the remaining 20% was set aside for testing. Such a split guarantees that the models being learned will only be evaluated on previously unseen interactions, which gives a trustworthy assessment of their generalization capability. Thanks to the user diversity, content richness, and the presence of temporal interaction data, the edX dataset stands out to evaluate context-aware and hybrid recommender systems in real-world e-learning environments.

B. Hyperparameters

The performance of the proposed hybrid recommender system strongly depends on the appropriate tuning of the hyperparameters of its three constituent modules, namely the SVD-based collaborative filtering model, the TF–IDF content-based model, and the LSTM-based contextual model. To ensure a fair and reproducible evaluation, the hyperparameters were selected through validation experiments and empirical tuning, balancing model complexity and generalization ability. The final configuration adopted for all experiments is reported in Table II.

For the SVD component, the number of latent factors controls the dimensionality of the user–item interaction space and directly influences the model's ability to capture hidden preference patterns. The learning rate and regularization term were carefully adjusted to ensure stable convergence and prevent overfitting, as summarized in Table II. In the TF–IDF module, parameters such as the n-gram range, vocabulary size, and document frequency thresholds were optimized to generate informative and discriminative content representations while reducing noise and sparsity.

For the LSTM-based contextual model, key hyperparameters, including the embedding dimension, number of hidden units, sequence length, dropout rate, and optimization settings, were tuned to effectively model temporal dependencies in learners' interaction histories without excessive complexity. These settings, detailed in Table II, enable the LSTM to capture evolving learning behaviors while maintaining stable and efficient training. Overall, the hyperparameter configuration reported in Table II ensures that the three modules operate in a balanced and complementary manner, allowing the hybrid framework to fully exploit collaborative, content-based, and contextual information in the recommendation process.

C. Evaluation Results and Discussion

Alongside evaluating the proposed hybrid recommender system's overall performance, we also examined its performance with and without contextual data. The results indicate that including contextual information considerably improves the system's effectiveness, as demonstrated in Fig. 2. While

Algorithm 1 Hybrid Recommendation System

```
Input: dataset, weights
Output: final_scores, precision, recall, ndcg, rmse
Step 1: Data Preprocessing
function PREPROCESSDATA(dataset)
    CLEAN dataset by handling missing values and outliers
    NORMALIZE numerical features to a uniform scale
    ENCODE categorical variables if required
    user_item_matrix = CREATE_USER_ITEM_MATRIX(dataset)            ▷ For CF
    textual_features = EXTRACT_TEXTUAL_FEATURES(dataset)           ▷ For CBF
    contextual_data = ORGANIZE_CONTEXTUAL_DATA(dataset)            ▷ For RNN
    return user_item_matrix, textual_features, contextual_data
end function
Step 2: Independent Model Implementations
function COLLABORATIVEFILTERING(user_item_matrix)
    [U, S, Vt] = SVD(user_item_matrix)
    predicted_ratings = PREDICT_RATINGS(U, S, Vt)
    rmse = CALCULATE_RMSE(predicted_ratings)
    return predicted_ratings, rmse
end function
function CONTENTBASEDFILTERING(textual_features)
    tfidf_matrix = COMPUTE_TFIDF(textual_features)
    similarities = COSINE_SIMILARITY(tfidf_matrix)
    ranked_courses = RANK_COURSES_BY_SIMILARITY(similarities)
    return ranked_courses
end function
function CONTEXTUALMODEL(contextual_data)
    sequences = PREPARE_SEQUENCES_FOR_RNN(contextual_data)
    rnn_model = TRAIN_RNN(sequences)
    context_predictions = PREDICT_WITH_RNN(rnn_model)
    return context_predictions
end function
```

Algorithm 2 Hybrid Recommendation System 2

```
Step 4: Result Aggregation (Weighted Hybrid)
function AGGREGATERESULTS(cf_scores, cbf_scores, contextual_scores, weights)
    final_scores = weights[0] * cf_scores + weights[1] * cbf_scores + weights[2] *
contextual_scores
    return final_scores
end function
Step 5: Evaluation
function EVALUATESYSTEM(final_scores, ground_truth)
    precision = CALCULATE_PRECISION_AT_K(final_scores, ground_truth)
    recall = CALCULATE_RECALL_AT_K(final_scores, ground_truth)
    ndcg = CALCULATE_NDCG(final_scores, ground_truth)
    rmse = CALCULATE_RMSE(final_scores, ground_truth)
    return precision, recall, ndcg, rmse
end function
```

session time, device type, user location, and interaction sequences are used as contextual data, this information helps the model to adapt its recommendations to the learner's situation, increasing engagement and the relevance of recommended courses.

The hybrid recommender system continues to achieve higher results across all the evaluation measures—Precision, Recall, F1-Score, and Mean Absolute Error (MAE)—than the baseline models [e.g., standalone Collaborative Filtering (CF) and Content-Based Filtering (CBF)], as shown in Fig. 3. The hybrid system results include, 0.75 precision, 0.68 recall, and 0.71 F1-score, while the CF results were 0.68 precision, 0.60 recall, and 0.63 F1-score, and CBF results were 0.70 precision, 0.64 recall, and 0.67 F1-score. The hybrid system delivered a 0.18 MAE, underscoring the improved predictive accuracy with the combination of user behavior and contextual data from the edX dataset. This compares to 0.21 with CF and 0.20 with CBF.

The hybrid framework, SVD-based CF, and deep learning-based (LSTM) models were additionally analyzed comparatively. Evaluation through all four primary metrics validates that, in most instances, the hybrid method performed best,

TABLE II. HYPERPARAMETERS OF THE SVD, TF–IDF, AND LSTM MODULES

Module	Hyperparameter	Description	Value / Setting
SVD (CF)	Latent factors (k)	Dimensionality of the user/item latent space	50
	Learning rate (η)	Step size for gradient updates	0.005
	Regularization (λ)	L2 penalty to reduce overfitting	0.02
	Epochs	Number of training iterations	50
	Initialization	Latent vector initialization strategy	Random (Gaussian)
	Loss function	Optimization objective for rating/implicit signal prediction	MSE
TF–IDF (CBF)	n-grams	Token range for feature extraction	(1,2)
	Vocabulary size	Maximum number of features retained	20,000
	Minimum document frequency (min_df)	Ignore rare terms below threshold	2
	Maximum document frequency (max_df)	Ignore overly frequent terms above threshold	0.90
	Normalization	Vector normalization scheme	L2
	Similarity metric	Similarity computation between course profiles	Cosine
LSTM (Context)	Embedding dimension	Size of interaction/context embedding	128
	Hidden units	Number of LSTM hidden neurons	128
	Number of LSTM layers	Depth of the recurrent network	1
	Dropout	Dropout rate for regularization	0.30
	Sequence length (T)	Number of past interactions used as input	20
	Batch size	Number of samples per training batch	64
	Optimizer	Optimization algorithm	Adam
	Learning rate	Step size for optimizer	0.001
	Epochs	Number of training iterations	30

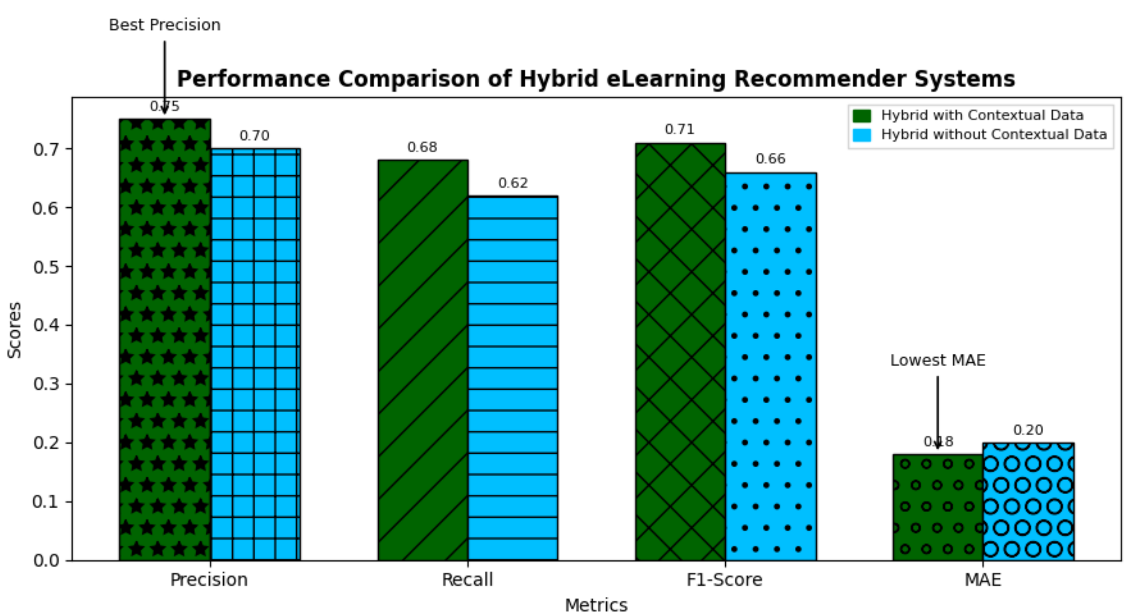

Fig. 2. Performance comparison of hybrid e-learning recommender systems.

TABLE III. COMPARATIVE PERFORMANCE OF RECOMMENDATION METHODS

Method	Precision	Recall	F1-Score	MAE
DL-based (NN)	0.73	0.66	0.69	**0.17**
SVD (Classic MF)	0.68	0.60	0.63	0.22
SVD + Tf-IDF + RNN (Our method)	**0.75**	**0.68**	**0.71**	0.18

see Fig. 4. For precision, the hybrid method achieved 0.75, ahead of the DL-based method's 0.73 and SVD's 0.68. The hybrid method also led in recall, attaining 0.68, greater than DL-based's 0.66 and SVD's 0.60, as shown in Table III. The hybrid system also achieved the best F1-score of 0.71, while the DL-based models scored 0.69 and SVD scored 0.63. The

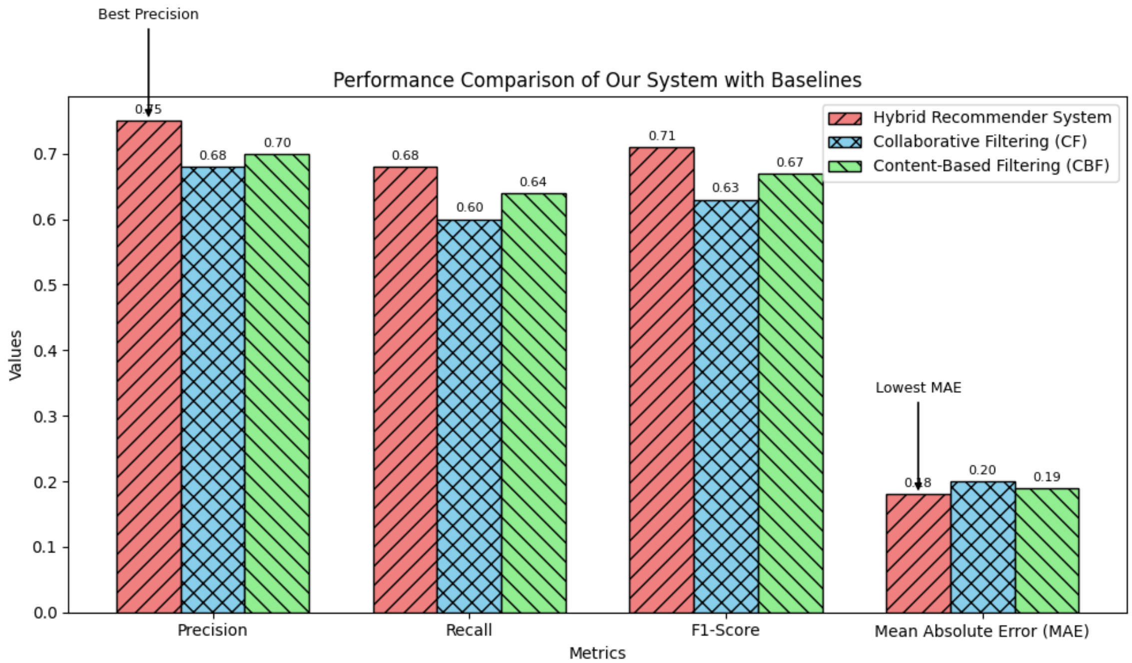

Fig. 3. Performance comparison of our system with baselines.

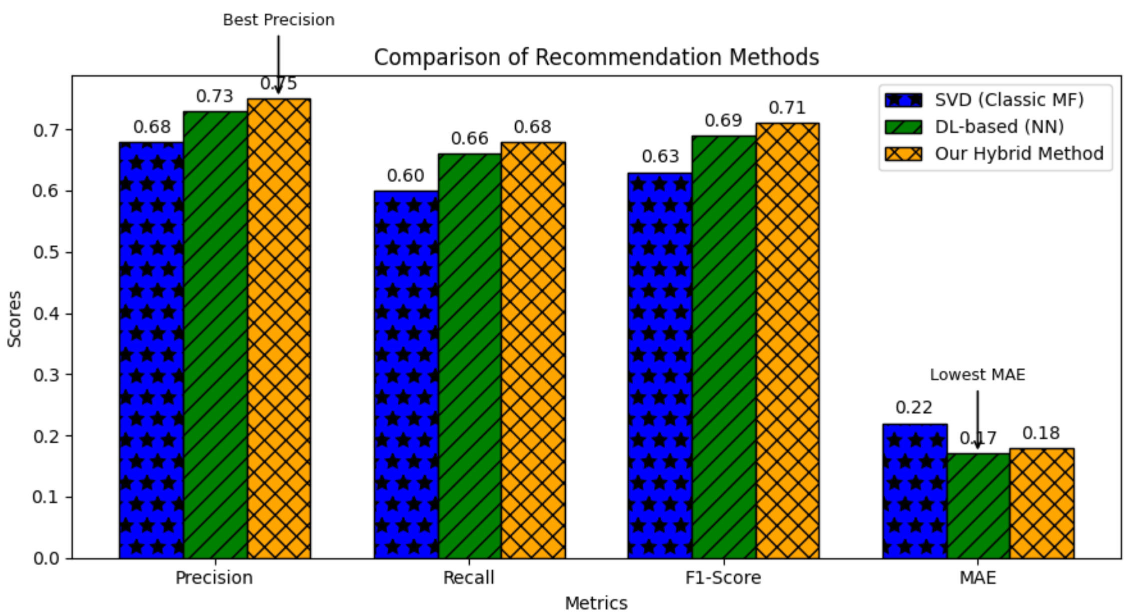

Fig. 4. Comparison of recommendation methods.

DL-based method had a slight edge in MAE, scoring 0.17, while the hybrid scored 0.18, and SVD scored 0.22. The hybrid system makes a balanced improvement by confirming active adjustments to the accuracy, as well as the error reduction, as it provides concrete evidence to the system's reliability and robustness.

As highlighted in this analysis, there are benefits to integrating CF, CBF, and contextual information. CF is good at predicting preferences based on user behavior, but it does not work well in the case of new users or courses with sparsely populated interaction history. CBF somewhat mitigates the cold-start problem, but is not able to adapt to shifting user behavior and situational dynamics. The hybrid approach improves on this by combining the methods with contextual data and producing suggestions based on learner preferences and situational constraints present in the real-world. For example, if users are engaged in short study sessions, the system suggests quick, shorter courses, while in the case of longer study sessions, it suggests comprehensive longer modules. This recommend system improves user satisfaction and engagement, which is especially important in the dynamic context of e-learning.

There are, however, unsolved issues. In some cases, sparse contextual data for user profiles, new users especially, or under-enrolled courses, may constitute a limit to system performance, even with contextual data augmentation. Furthermore, the need to combine multiple data sources poses a significant challenge in terms of real-time recommendations. This is likely due to the system requiring excess processing power on large platforms like edX, making it a scalability barrier. Future work could target this problem by optimizing, for example, distributed computing or incremental learning coupled with lightweight neural nets to improve processing speed while preserving the quality of the recommendations.

Enriching the contextual data surrounding users in an e-learning environment increases the value of the recommendations provided. While recommender systems like Collaborative Filtering (CF) and Content-Based Filtering (CBF) offer the basics of personalized recommendations based on historical interactions or static content features, they do not capture the dynamic situations the learner is in. Thousands of interactions provide contextual data on patterns, such as duration of content sessions and timing of access, while device type and geo-location add further dimensions. By these measures, the hybrid recommender system is able to escape the proposition of static recommendations and deliver relevant and actionable suggestions based on the learner's context.

Precision and relevance of the recommendations are enhanced with the addition of contextual data. For instance, learners accessing the platform when taking short breaks would appreciate brief modules or quick tutorials. In contrast, learners engaging in longer study periods are eligible for more extensive courses or multi-part learning paths. This temporal and situational awareness can make recommendations relevant for learners, focusing on their attention spans and immediate needs. This increases the probability of completion and active utilization of recommended courses. Real-time adaptation to changes in conditions creates unprecedented flexibility, accommodating user behavior and preferences, and external limitations, and their behavioral and contextual changes without requiring overriding manual control.

Learning contextual data enhances learner motivation and engagement. Improved engagement and motivation primarily stem from the interaction of contextual information with the designed learning activities. Users are more likely to continue engaging with the platform when contextual data is incorporated into the recommendations. The hybrid system's ability to incorporate contextual factors creates a purposeful and meaningful learning environment that enhances immersion and satisfaction.

Incorporating context-aware hybrid recommender systems sets a new standard in personalized e-learning. Differing from conventional models that rely on fixed features or merely historical features, these systems dynamically adjust to learners as they progress, updating suggestions in real-time with contextual and behavioral information. Such flexibility is important in real e-learning systems to ensure compatibility with varying user demographics and learning situations. Use hybrid systems maximize contextual information; they effectively improve outcomes, adjust learning personalization and support high flexibility educational systems, paving the way for advanced smart educational frameworks.

V. Conclusion

This work was the first to combine Collaborative Filtering, Content-Based Filtering, and Contextual Data Modeling into a hybrid e-learning recommender system to create context-aware, personalized e-learning course recommendations. Using the additional and overlapping strengths of the aforementioned frameworks decreased some of the major drawbacks of conventional recommender systems, including underexploited cold-start and data sparsity situations, excessive overspecialization of recommendations, and a failure to address shifting user needs and preferences. Some of the advanced algorithms implemented in this hybrid system include Singular Value Decomposition (SVD) for latent factor analysis, TF-IDF for content feature extraction, and Long Short-Term Memory (LSTM) networks for temporal and contextual user behavior modeling.

The hybrid system, which was evaluated on the edX course dataset, consistently surpassed solo CF and CBF baseline models on metrics such as precision, recall, F1 score, and Mean Absolute Error (MAE), as well as on multiple other metrics. Contextual data such as the user's device, session duration, and location accessed data, which was incorporated into the system, significantly improved the precision and utility of the recommendations. Lastly, the fusion mechanism, which integrates the disparate evaluation systems within each of the three components, offers the system a high degree of flexibility and robustness in addition to balance, accuracy, diversity, and adaptability in its recommendations.

Research contributions are as follows: First, this work presents a unified hybrid framework combining collaborative, content-based, and context-aware strategies for e-learning. Second, this work illustrates the synergistic use of SVD, TF-IDF, and LSTM in tackling common problems in recommendation systems. Third, this work uses educational real-world data as evidence that the proposed framework offers a more personalized approach to recommend courses and improves the overall learning experience.

Although there are achievements, limitations and challenges still exist. The system in use is guided by historical and contextual data which may not be complete and accurate, and real-time adaption to user behavior shifts and cross-platform access still can be improved. Furthermore, the protective use of real-time contextual and behavioral data and the systems' data acquired for situational context reveals core challenges of privacy and security.

Subsequent work will target the use of reinforcement learning and deep learning because they can enhance the systems understanding of nuanced user preferences and advanced sequence of learning patterns. The system will be more personalized by incorporating learner goals, motivation, and affect. Finally, system extensibility to permit multi-platform systems, in conjunction with the use of privacy-conscious strategies for system deployment in e-learning environments is imperative for system's ethical and responsible scalability.

The proposed hybrid and context-aware recommender system represents a strong, adaptable, and extensible approach to personalization in e-learning. Incorporating elements of collaborative, content-based, and contextual mechanisms yields not only enhanced precision and pertinence in recommendations but also sets a foundation for more sophisticated, evolving, and learner-focused approaches to education in the digital age.

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