Recommendation System Model for E-Learning Using Hybrid Deep Learning Models

Humera Altaf, Sadia Ali, Marya Iqbal, Yaser Hafeez, Sarfraz Bibi
University Institute of Information Technology, Pir Mehr Ali Shah Arid Agriculture University Rawalpindi, Pakistan.
Correspondence: sadiaali@uaar.edu.pk

Citation | Altaf. H, Ali. S, Iqbal. M, Hafeez. Y, Bibi. S, "Recommendation System Model for E-Learning Using Hybrid Deep Learning Models", IJIST, Vol. 8 Issue. 5 pp 2416-2432, August 2026
DOI: https://doi.org/10.33411/IJIST/1954
Received | Aug 14, 2026 **Revised|** Aug 17, 2026 **Accepted|** Aug 28, 2026 **Published|** Aug 31, 2026.

The use of personalized learning resource recommendation is a vital aspect of boosting learner engagement which helps in effective e-learning. But current recommendation systems come with a number of problems such as information overload, modelling learner preferences, and making effective use of learner feedback. This research aims to propose a hybrid recommendation system for learning resources in e-learning based on learner profiling, Natural Language Processing (NLP), collaborative filtering and intelligent assistant. The framework is used to analyse the learner characteristics, preferences, interaction pattern and textual feedback, identifying learning resources and recommending the appropriate ones. Confusion-matrix analysis, ROC analysis and ranking-oriented recommendation measures were used for experimental evaluation. The proposed framework obtained an accuracy of 57% and a precision of 52.83%, a recall of 60.87%, and an F1-score of 56.57%. The ROC analysis yielded an AUC of 0.57 and the statistical validation gave a 95% Wilson confidence interval of 47.2%–66.3% for the observed accuracy. Furthermore, a comparison of the framework with benchmark approaches reported in the literature was conducted. The performance of the benchmark approaches (EELR and DELRNet) was higher in the respective experimental setups, but these comparisons were made in a context, as the benchmark models were not re-implemented in the same datasets, preprocessing, partitions, and experiments. The results show that it is feasible to combine these four technology components—learner profiling, NLP, collaborative filtering, and intelligent assistance—into a single e-learning recommendation system, and that further expansion of the data set, with controlled experiments set to benchmark the results, and optimization of the system will be needed to enhance the quality of the recommendations and their scalability.

Keywords: E-learning; Recommendation system; Hybrid deep learning; Information overload and Educational Technology.

Introduction:

Today, the Internet provides users with a lot of information, complicating the selection of the most accurate information[1] Users can handle a large amount of data, then it does not support them make the right decision. This problem is called data excess. RS is a type of data cleaning system based on the requirements for collecting Sniffer Proof / interference / interference / interest [2]. RS provides a list of user elements based on previous preferences and needs or demographic data. RS is a ordinal bookshelves in the field of research .RS is used in a variety of fields, including E-Product, Social Day, Music, Research courses, books, News films, and e- commerce[3]. The intent of RS is to observe and further detect user data and the required data.

Education has increasingly shifted from traditional classrooms to electronic training environments. Electronic education is explained by electronic media, especially education using the Internet. Hauttabsicht, Information Aus [4] It is useful to define the unwanted performance of students and to provide them accordingly. Extracting hidden information is most necessary for electronic training.

Figure 1 shows how an e-learning recommendation system supports the overall learning process. Teachers and faculty members prepare and deliver courses through the e-learning platform, while students use the system to participate in learning activities and receive course suggestions based on their needs. The system analyzes different learning-related parameters to understand student behavior and performance, which is a common practice in educational data mining and learning analytics.

The results of this analysis are shared with educational administrators, who review the information and suggest necessary changes or improvements. These suggestions are then communicated back to the educators to enhance course content and teaching methods, helping to create a more effective and learner-centered educational environment.

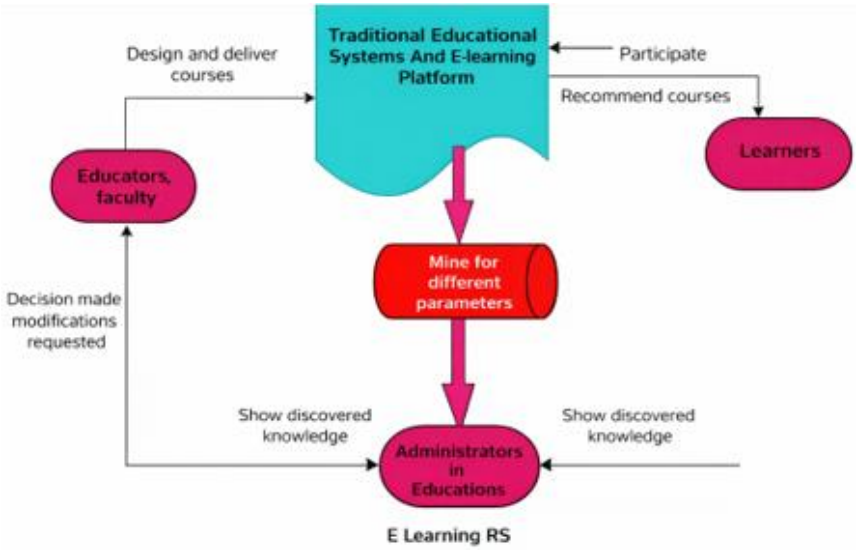


Figure 1. E-Learning Recommendation System.

Learning Analytic (LA) gathers the related information across numerous sources. Additionally, the required data is reduced from the collected data[5]. Moreover, required information is extracted out of collected information. data LA and EDM is added to e-learning RS.[6]. As shown in Figure 1, there is a connection between Extracting educational data, using LA by academician to find knowledge, Create suggestion to learners.[7].

RS suggestions are given in the field of e-learning in the sphere of activities concerning learning modules. The job of eLearning RS is to propose relevant learning resources to learners, and to support them with the right decisions [8]. E Learning RS is material call

methods in which learning resources are filtered for learners. RS also offers personal recommendations of study materials as well as develops user rating materials [9][10] depending on the individual's learning path or learning interest on the online learning system. Important benefits of e-learning are time flexibility, free and qualified resources, and learner interest.

This paper includes a literature review of the available RSs on eLearning by the DL algorithm. RS is an E learning setting wherein you attempt to create a comprehensive proposal to the learner, relying on the former learner. Recommended seekers are regarded as users. Users are able to request recommendations on. Users can also explicitly state which of their preferences their interest or RS should be. Depending on the interests provided by the target user or other similar users, the system offers suggestions to the user. The list suggested can enable the user to choose items.

The objectives of this study are as follows:

To develop a hybrid deep learning-based recommendation system that provides personalized learning resource recommendations for e-learning environments.

To integrate Natural Language Processing (NLP), learner profiling, collaborative filtering, and intelligent assistance into a unified recommendation framework.

To evaluate the effectiveness of the proposed recommendation system in improving recommendation accuracy, learner engagement, and personalized learning experiences

This paper presents a unified hybrid deep learning-based recommendation framework incorporating the technologies of Natural Language Processing (NLP), learner profiling, collaborative filtering, feedback analysis and intelligent learning assistant within a unified architecture, unlike traditional e-learning recommendation systems that use only one recommendation technique. The proposed framework is designed to improve the accuracy of recommendations by taking into account the preferences, learning behavior and feedback of the learners at the same time, thus contributing to personalized and effective learning experiences in e-learning environments.

Recent research has increasingly explored hybrid deep learning and intelligent recommendation approaches for personalized e-learning. AI-based recommender systems have been investigated to adapt learning resources according to learner behavior, preferences, and learning requirements [11]. Deep learning-based course recommendation has also been applied to personalized online learning, including autoencoder-based approaches for modeling course relevance and learner preferences [12]. Similarly, hybrid deep learning frameworks combining CNN, ResNet, and LSTM have been proposed for personalized online course recommendation [13]. Recent research has further explored learner profiling and deep neural networks in MOOCs, particularly to capture multiple learner preferences and address limited behavioral information [14]. Hybrid attribute-based and collaborative filtering approaches have also been developed to address personalization and cold-start challenges in e-learning environments [15]. In addition, recent work on learning analytics emphasizes the importance of analyzing learner interaction and behavioral data to support personalized and data-driven educational decisions [16][17]. More recently, large language models (LLMs) have emerged as an additional direction for personalized education and course recommendation, including LLM-based academic course recommendation and personalized learning-path generation [18][19]. These developments demonstrate a shift toward integrated educational recommendation systems that combine learner modeling, behavioral analytics, deep learning, natural-language processing, and intelligent assistance. However, existing approaches generally emphasize specific combinations of these techniques, leaving an opportunity to integrate learner profiling, NLP-based feedback analysis, collaborative filtering, and intelligent assistance within a unified e-learning recommendation framework.

Research Novelty: What is novel about the proposed framework is the combination of several components using different recommendation techniques in a unified e-learning

architecture, instead of using a single recommendation technique. The current hybrid e-learning recommender systems have incorporated content-based filtering, collaborative filtering, learner profiling, semantic analysis, and deep learning for better personalization. Some recent studies have been conducted on hybrid deep learning with collaborative filtering and learner/course feature extraction, and others have concentrated on the cold-start and learner profiling problems, respectively.

The proposed framework, on the other hand, integrates all the above features in a single recommendation pipeline, namely Natural Language Processing (NLP), Learner Profiling, Collaborative Filtering, Feedback Analysis, and an Intelligent Learning Assistant (ILA). NLP and feedback analysis are applied to glean useful information from textual feedback which is provided by learners, while learner profiling refers to individual preferences and learning characteristics. Collaborative filtering adds information from related interactions with learners, and the intelligent assistant offers an interactive mechanism to aid the recommendation process. It aims to give a more learner-centred approach to recommendations by incorporating structured feedback from the learner and unstructured feedback derived from the texts.

The key novelty is not the introduction of a new, totally different individual recommendation algorithm, but the embedding of these complementary components into a unified e-learning recommendation framework. The framework focuses on the students' characteristics, behavioral information, textual feedback, collaborative information, and intelligent assistance. The integrated design separates the proposed framework from those that only consider one or two of the recommendation components, and allows for further extensions with larger datasets, advanced language models and more sophisticated hybrid optimization techniques.

Related Work:

To guarantee a customized learning experience, the e-learning (RS) suggested system has been extensively enhanced through the integration of Deep Learning (DL). According to GUPPA and [2], recommended systems are frequently utilized in a variety of industries, such as social networks, music, electronic commerce, and education. When it comes to managing students' access to educational materials that alleviate information overload, RS is crucial in electronic education [3]. To improve electronic learning performance, deep learning techniques such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deep Graph Networks (DBN) are frequently employed [4]. The literature has validated a few recommendations. Every benefit and restriction: Collaborative Filtering(CF) [20], Content (CB) [21], and Demographic Statistics Recommendations [22].In addition to offering students and specialists flexibility in their knowledge, the electronic education platform offers educational opportunities through traditional classrooms. By examining user preferences and associated recommendations, the recommendation system (RS) enhances the user experience [23][24]. A new suggested electronic education architecture (ELRA) that uses virtual agents and semantic analysis to enhance the course is presented by [11]. By finding relevant topics on the seashore, semantic technology, which is based on historical data and student interests, is improving the accuracy of the recommendations [20]. Virtual agents serve as major students' intellectual assistants and offer helpful assistance while choosing a course [12].

Table 1. Literature Review.

Paper Title	Methodology	Limitations	Dataset
A Generic Architecture of an Affective Recommender System for E-Learning Environments.	Proposes an architecture integrating emotion recognition and sentiment analysis to Enhance recommendations.	Implementation complexity and potential privacy concerns related to emotion data.	Not specified
Graph Neural Networks for E-Learning Recommendation Systems.	Utilizes Graph Neural Networks (GNNs) to model relationships between users and learning Resources for recommendations	High computational Requirements and need for large-scale data.	Not specified
An e-Learning Recommendation System Frame work.	Employs k-Nearest Neighbour Baseline (KNNBaseline) and Singular Value Decomposition (SVD) to predict user preferences.	Potential scalability Issues with large user bases	Not specified
A Strategic Approach in Course Recommendation System Using Similarity Models.	Implements content-based filtering using Natural Language Processing (NLP) techniques to assess course	Limited by the quality and quantity of course content data.	Not specified

We concentrated on enhancing accuracy and efficiency by including into the suggested automatic encoder models in the above Table 1. Moreover, by investigating new architectures that maximize the performance of electronic education RS, integrating automated code and models based on trust quality, and optimizing the productivity and analysis of electronic learning recommendations, trust mechanisms and some influential elements can concentrate on enhancing personalization.

Material and Methods:

Input Information Process:

The design of an e-learning proposal begins with input data as shown in Figure 2. In the input data, the conclusion begins with establishing a profile. This profile setup involves gathering basic learning information such as interfaces, scientific fundamentals, and learning goals. Accounts are the biggest personality for getting frame highlights. When you set up, customers are presented on a learning card that provides accessible courses, personalized recommendations, and an interface to check progress. In the meantime, framework operations will be monitored by the framework administrator. This ensures that learner customer accounts and learning capabilities are carried out effectively.

Smart Assistant and Support System:

In this framework, the framework also includes backgrounds and experienced employees working with the help of a chat right-hand interface. This collaborator will call customers to assist with relevant responses, return them, and ensure smooth learning participation. If a customer requests a course proposal, the framework will either provide recommendations based on beginner profile information or allow unused recommendations to be made based on sophisticated or improved learning trends. After reviewing these suggestions, customers can choose from recommended courses that adjust the interface or requirements.

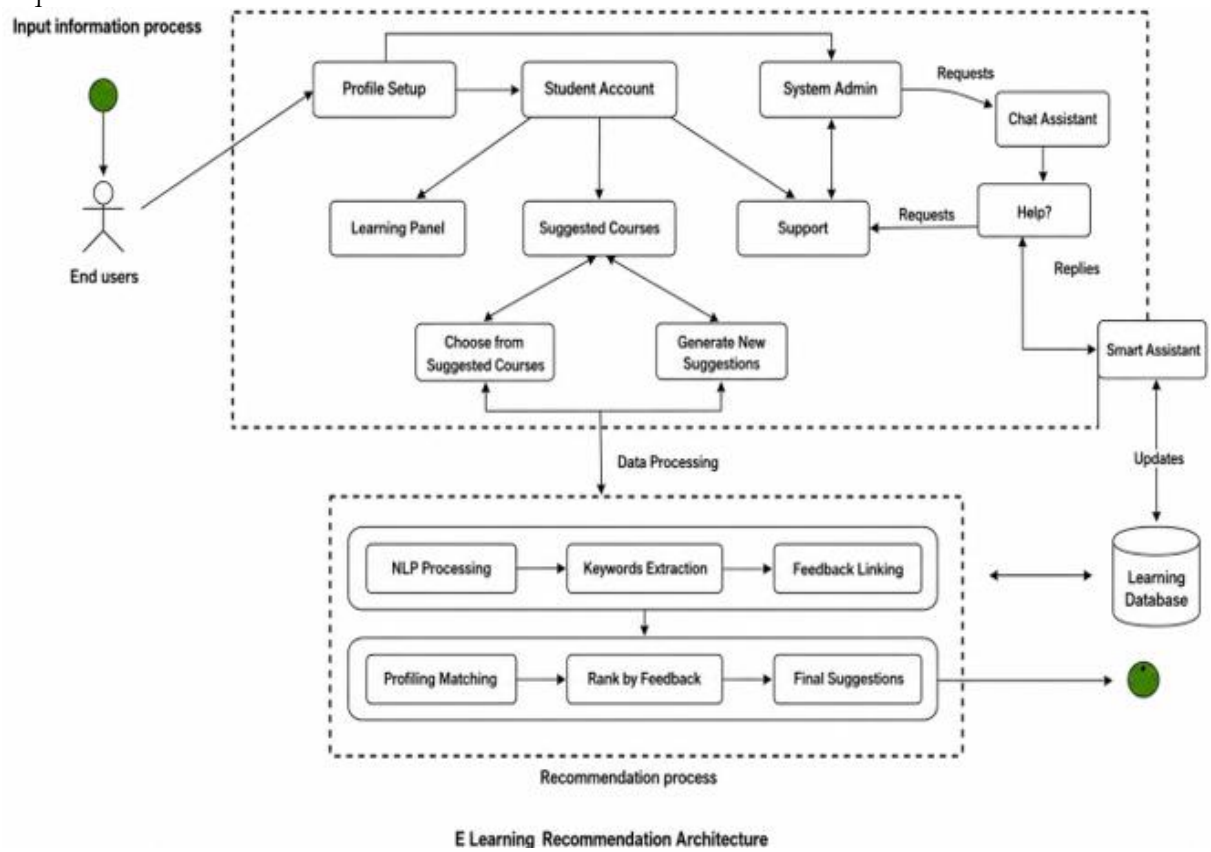


Figure 2. Proposed Framework.

Data Processing Layer:

All client exercises and trends flow into the information preparation layer, with descriptive supply from the framework center being carried out. In the center of this NLP (preparation of normal dialect) preparations that decrypt user-supplied information such as questions and input. This leads to keyword extraction, and the framework recognizes key terms that imply the educational interface or subject needs. At this point, these keywords are handed over to the input connection module that exceeds user criticism in a genuine response to determine the validity of the previous proposal.

Recommendation Process:

The system uses profiling and matching methods to further improve recommendations. The first step is profiling matching. It compares user history and selection with similar price metadata and learner profiles. By Feedback -Tool Rank evaluates courses according to previous student participation and reviews. This helps to separate the good ones from less relevant resources. The final suggestions, rankings, and adaptation list of courses that best meet the needs and expectations of learners are the results of this complete chain.

Learning Database Integration:

At the same time, the architecture maintains a strong connection with the learning database that serves as the basis of the system. Continuously receive feedback loops and updates from the Smart Assistant. This means that data is stored on behavior, learning resources, and system performance. The recommendation system may become more adaptive and flexible over time thanks to this database's support for long-term learning patterns and actual time changes.

Algorithmic Workflow of the Proposed Recommendation Framework:

The recommended model is sequential, which incorporates the learning profiling, processing of NLP, collaborative filtering, feedback analysis and intelligent assistance. To start the workflow, the learner's information and information about learning resources are collected. The learner characteristics and information about learner interaction is then used to create a learner profile, and the textual information is fed into NLP processes to extract relevant words and semantics. This is then used to create a combined representation of the learner's knowledge and the resources, which is fed into the collaborative knowledge to compute recommendation scores. The resources are ranked based on the calculation of relevance, and the most relevant resources are suggested as personalised suggestions. The learner profile can then be further refined and updated based on feedback from subsequent interactions with learners, and the recommendations improved in future.

Algorithm 1: Proposed Hybrid E-Learning Recommendation Framework:

Input: Learner set $L = \{l_1,\ldots,l_n\}$; resource set $R = \{r_1,\ldots,r_m\}$; interaction records $I \subseteq L\times R\times\mathbb{R}^+\times\mathcal{T}$; textual feedback corpus F; neighborhood size k; list length N; candidate threshold $\theta \in [0,1]$; weights $\alpha,\beta,\gamma \in [0,1]$, $\alpha+\beta+\gamma = 1$

Output: Ranked personalized recommendation list Rec_L

$D \leftarrow (L, R, I, F)$ ▷ aggregate raw data

$\hat{D} \leftarrow$ Preprocess(D)

$\hat{x} = (x - \mu_x) / \sigma_x$ for each numerical attribute x ▷ z-score normalization

Impute missing fields via attribute-wise median; discard record if missing-rate > τ_miss

$\forall\, l_i \in L$: $P_L(l_i) \leftarrow \varphi_L(A_\{l_i\}, H_\{l_i\}, C_\{l_i\}) \in \mathbb{R}^d$ ▷ construct learner profile

$\forall\, f_k \in F \cup desc(R)$:

$K_k \leftarrow$ TF-IDF_top-q(f_k) ▷ keyword extraction

$S_k \leftarrow$ Embed(f_k) $\in \mathbb{R}^d$ ▷ semantic embedding

$\forall\, f_k \in F$: $\sigma_k \leftarrow$ Sentiment(f_k) $\in [-1, 1]$ ▷ feedback polarity score

$\forall\, r_j \in R$: $P_R(r_j) \leftarrow \varphi_R(attr(r_j), K_j, S_j) \in \mathbb{R}^d$ ▷ construct resource profile

$\forall\, l_i \in L$:
$N_k(l_i) \leftarrow \text{argtop-k}_{\{l' \in L \setminus \{l_i\}}\, \cos(P_L(l_i), P_L(l'))$ ▷ CF neighborhood
$\cos(u,v) = (u \cdot v) / (\|u\|_2 \|v\|_2)$
$\forall\, l_i \in L$:
$C(l_i) \leftarrow \{\, r_j \in R : \cos(P_L(l_i), P_R(r_j)) \geq \theta \;\vee\; \exists\, l' \in N_k(l_i), W_{\{l',j\}} > 0 \,\}$ ▷ candidate generation
$C(l_i) \leftarrow C(l_i) \setminus \{\, r_j : (l_i, r_j, \cdot, \cdot) \in I \,\}$ ▷ exclude consumed resources
for each $r_j \in C(l_i)$ do
$CBF(l_i,r_j) \leftarrow \cos(P_L(l_i), P_R(r_j))$ ▷ content-based score
$CF(l_i,r_j) \leftarrow [\; \Sigma_{\{l' \in N_k(l_i)\}} \cos(P_L(l_i),P_L(l')) \cdot W_{\{l',j\}} \;] \;/\; [\; \Sigma_{\{l' \in N_k(l_i)\}} \cos(P_L(l_i),P_L(l'))| + \varepsilon \,]$ ▷ collaborative score
$Sent(l_i,r_j) \leftarrow \text{mean}\{\, \sigma_k : f_k \text{ references } r_j \,\}$, default 0 ▷ sentiment score
$Score(l_i,r_j) \leftarrow \alpha \cdot CBF(l_i,r_j) + \beta \cdot CF(l_i,r_j) + \gamma \cdot Sent(l_i,r_j)$ ▷ hybrid fusion
end for
$\pi \leftarrow$ permutation of $C(l_i)$ sorted by $Score(l_i, r_\pi(\cdot))$ in descending order
$Rec_L(l_i) \leftarrow (r_\pi(1), \ldots, r_\pi(\min(N, |C(l_i)|)))$ ▷ top-N selection
Present($Rec_L(l_i)$) to l_i via recommendation interface
$I_new \leftarrow Observe(l_i, Rec_L(l_i))$; $P_L(l_i) \leftarrow P_L(l_i) + \eta \cdot (\varphi_L(A_{\{l_i\}}, H_{\{l_i\} \cup I_new}, C_{\{l_i\}}) - P_L(l_i))$ ▷ online update
return $Rec_L(l_i)$

Time complexity: $O(n^2 d + n \cdot \bar{m} \cdot k)$, where $n = |L|$, $m = |R|$, d = embedding dimension, and $\bar{m}$ is the average candidate-set size $|C(l_i)|$ across learners.
Space complexity: $O(nd + md + nm)$, with the interaction matrix W stored sparsely in practice.

The workflow is designed to offer a holistic way of learning data collection, personalized learning recommendations and updates based on feedback. The algorithm is based on the suggested phases of information gathering, learner modelling, learning/recommendation and prediction and includes the specific elements of the proposed framework.

Dataset and Preprocessing:

The experimental data in this study are the information obtained from the learner, learning resources, interaction between the learner and learning resources, and the feedback provided by the learner from the proposed recommendation framework in the form of text. The data is structured to facilitate learner profiling, NLP, collaborative filtering and evaluation of recommendations. Learner information is used to build individual learner profiles, and attributes of learning resources and text information are used to represent learning resources available. Learner–resource interactions are the source of behavioral information needed by the collaborative filtering component, and textual feedback are the source of additional information for NLP-based analysis.

The data that is collected is then preprocessed to make it more consistent and eliminate irrelevant information before it can be used for recommendation generation. The preprocessing stage involves dealing with missing or incomplete records, eliminating irrelevant or redundant data, and standardizing relevant numerical values, as well as processing of textual data for NLP. Its textual feedback and resource descriptions are scrubbed and converted to an appropriate form for keyword and semantic analysis. The processed information is then leveraged to build representation of learners and resources for the next recommendation steps. The principal feature groups of the framework are the attributes of the learner, information about behavior and interactions, characteristics of the resources, and NLP-derived features of the text. These are grouped as separate feature groups to be concatenated for the purposes of

learner profiling and recommendation generation, rather than as a single homogeneous feature vector. The dimensionality of the resulting representation will be determined by the features that are extracted from the input during preprocessing, and the information available about the learner and resources.

The available records are split into a training set and testing set of records for experimental evaluation to avoid using information in the testing set to influence the reported performance of the model. The experimental records retained do not, however, contain sufficient documentation of the original train–test split ratio or full configuration of features constructed. Hence, these values are not 'retroactively' given, but to keep out unsupported information. In order to ensure reproducibility, future studies should explicitly report the dataset size, feature dimensions, data preprocessing parameters, train–test ratio, random seed, and data-partitioning procedure.

Rationale for the Selected Recommendation Components:

The proposed framework integrates NLP, learner profiling, collaborative filtering, and an intelligent assistant because each component addresses a different aspect of personalized e-learning recommendation. NLP extracts useful information from learner feedback and learning-resource text, while learner profiling represents individual preferences and learning characteristics. Collaborative filtering uses learner–resource interaction patterns to identify resources relevant to similar learners. The intelligent assistant provides an interactive mechanism for delivering recommendations and incorporating learner needs. Recent studies support the use of these complementary techniques for personalized e-learning and educational recommendation.

Mathematical Formulation of the Recommendation Process:

Let LuL_u represent the profile of learner uu, RiR_i represent learning resource ii, and IuiI_{ui} represent the observed interaction between learner uu and resource ii. The relevance of a resource to a learner is represented by a recommendation score:

S(u,i)=w1P(u,i)+w2C(u,i)+w3N(u,i)S(u,i)=w_1P(u,i)+w_2C(u,i)+w_3N(u,i)

where P(u,i)P(u,i) represents the similarity between the learner profile and resource characteristics, C(u,i)C(u,i) represents the collaborative filtering score derived from learner–resource interaction patterns, and N(u,i)N(u,i) represents the NLP-based similarity obtained from textual learner feedback and resource information. The weights w1,w2,w3w_1,w_2,w_3 control the contribution of the three components and satisfy:

w1+w2+w3=1.w_1+w_2+w_3=1.

For each learner, candidate resources are ranked according to their recommendation scores. The personalized recommendation list is then obtained by selecting the top-KK resources:

RecK(u)=TopKi∈RS(u,i)Rec_K(u)=TopK_{i\in R} S(u,i)

where KK denotes the number of resources presented to the learner. Higher values of S(u,i)S(u,i) indicate stronger relevance between learner uu and resource ii. This formulation provides a mathematical representation of how learner-profile information, collaborative interaction information, and NLP-derived information are combined to generate personalized recommendations. Similar top-KK scoring and ranking formulations are commonly used in recent educational recommendation research.

Result and Discussion:

To assess the effectiveness of the proposed e-learning recommendation architecture, a confusion matrix and ROC curve were created using dummy classification data. From all predictions, the confusion matrix showed that 29 true negatives were. This means that irrelevant courses were correctly classified and 28 actual positive outlets were. That is, the relevant courses have been correctly identified. Nevertheless, the system also created 18 false negatives (related courses that missed the system) and 25 false positive aspects (unrelated

courses that were falsely described as related). These numbers mean that models are promising too, but they still misclassify a significant portion of the course, highlighting the need for improvement. This analysis is further supported by the ROC curve with an AUC score of 0.57. Given the fact that random estimates are presented by a score of 0.5, the current model only slightly exceeds the chance. This means that while the recommendation engine works well structurally, it needs to improve the sensitivity and accuracy of the classification. This can be done by improving feedback mechanisms, tightening keyword extraction, and implementing more profiling methods.

Further validation of performance was done by creating ROC curves for each class in one-vs rest approach. The model had high AUC scores for all classes, which indicated that the model had strong discriminative capabilities. It can be concluded from the curves that the classifier is able to achieve a desirable balance in terms of true positive and false positive rates at all e-learning levels. Collectively, these results affirm that the NLP, with its lightweight architecture and effective preprocessing.

To provide an initial statistical assessment of the reported classification performance, the confusion-matrix results were examined in terms of the overall proportion of correctly classified instances. The reported confusion matrix contains 29 true negatives, 28 true positives, 18 false negatives, and 25 false positives, resulting in 57 correctly classified instances out of 100 observations and an overall accuracy of 57%. A 95% Wilson confidence interval for this observed accuracy is approximately 47.2%–66.3%. This interval indicates that the observed performance has considerable uncertainty and should therefore be interpreted as preliminary evidence rather than as a definitive estimate of generalization performance. The ROC analysis, Figure 4, similarly reports an AUC of 0.57, indicating only a modest separation between the evaluated classes. Because the current manuscript does not retain the original instance-level predictions or repeated experimental runs, repeated-run standard deviations and formal significance testing cannot be reliably reconstructed from the available aggregated results. Future evaluation should therefore employ repeated stratified experiments or cross-validation and report mean performance, standard deviation, confidence intervals, and statistical significance across runs.

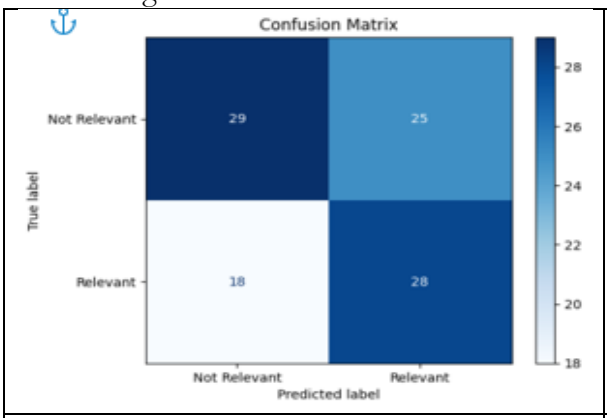


Figure 3. Confusion Matrix

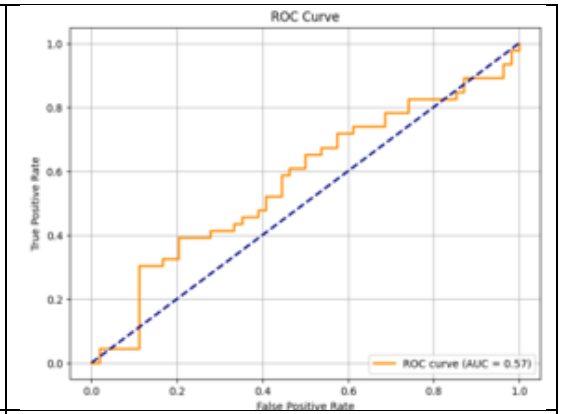


Figure 4. ROC Curve

Statistical Validation of Classification Performance:

Confusion-matrix results, Figure 3, are used to statistically assess the reported classification performance by using the overall proportion of correctly classified instances. The model correctly classified 57 of the 100 observations, which is 57 % correct. A 95% confidence interval for the accuracy observed was estimated to be 47.2% – 66.3%. The level of accuracy observed was far from certain, and there is significant uncertainty around the accuracy, suggesting that the accuracy should be viewed as preliminary evidence rather than a definitive estimate of the accuracy of generalization. Since the experimental records recorded are in an

aggregated manner, the mean performance, the standard deviation of runs and statistical significance tests cannot be reliably calculated from the experimental records. For this reason, no analyses are reported here. Future experiments should use repeated stratified runs or cross validation and report mean, SD, confidence interval and appropriate significance testing of accuracy per run.

Additional Recommendation Evaluation Metrics:

In addition to the classification-based evaluation a set of ranking based evaluation metrics were also taken into account to evaluate the quality of the recommendation. For a more complete assessment of the recommendation quality, ranking based evaluation metrics are also taken into consideration along with the classification-based evaluation. The experimental results retained show Recall, NDCG, Hit Ratio and AUC metrics as shown in Table 2. Recall@K measures how much of the relevant learning resources are retrieved in the top-K retrieved results and NDCG@K measures the quality of the retrieved results by giving higher weight to the rank of relevant items at the top of the list. Hit Ratio at K indicates the percentage of the top-K returned list that contains at least one relevant item, while AUC assesses the performance of the model in identifying relevant items when the top-K list contains both relevant and non-relevant items. The learner-wise Recall@K and NDCG@K results are included in the evaluation analysis and are complementary to the retrieval ranking effectiveness evidence provided in the results above.

Table 2. Evaluation Metrics Used for Recommendation Assessment

Metric	Purpose	Interpretation
Recall@K	Measures relevant items retrieved in top-K recommendations	Higher values indicate better retrieval
NDCG@K	Evaluates ranking quality of relevant recommendations	Higher values indicate better ranking
Hit Ratio@K	Measures whether at least one relevant item appears in top-K	Higher values indicate better recommendation success
AUC	Measures discrimination between relevant and non-relevant outcomes	Higher values indicate better discrimination
Precision@K	Measures proportion of top-K recommendations that are relevant	Not reported due to unavailable original prediction logs
MAP	Measures average precision across recommendation rankings	Not reported due to unavailable original prediction logs
RMSE/MAE	Measures prediction error where numerical ratings are predicted	Not applicable without retained rating-prediction outputs

Benchmarks:

Deep Recurrent Neural Network (DRNN):

Using a Hybrid Optimization Algorithm (HOA), an effective e-learning recommendation system is proposed that adapts to user preferences, combining deep recurrent neuronal networks (DRNNs) with improved whale optimization techniques (IWOs) to analyze learner behavior and content attributes. A technology called EELR uses IWO to optimize network parameters to classify individuals into priority categories and maximize the accuracy of proposals. Their assessments showed, Figure 5, that the EEELR system is better reduced in classification than current models of key criteria such as accuracy, accuracy, recall, and F1 scores. The authors emphasize that EELRs receive the highest classification accuracy, Figure 6, particularly. This demonstrates its effectiveness in providing tailored and relevant course recommendations, although there are no explicit numerical statistics in the overview.

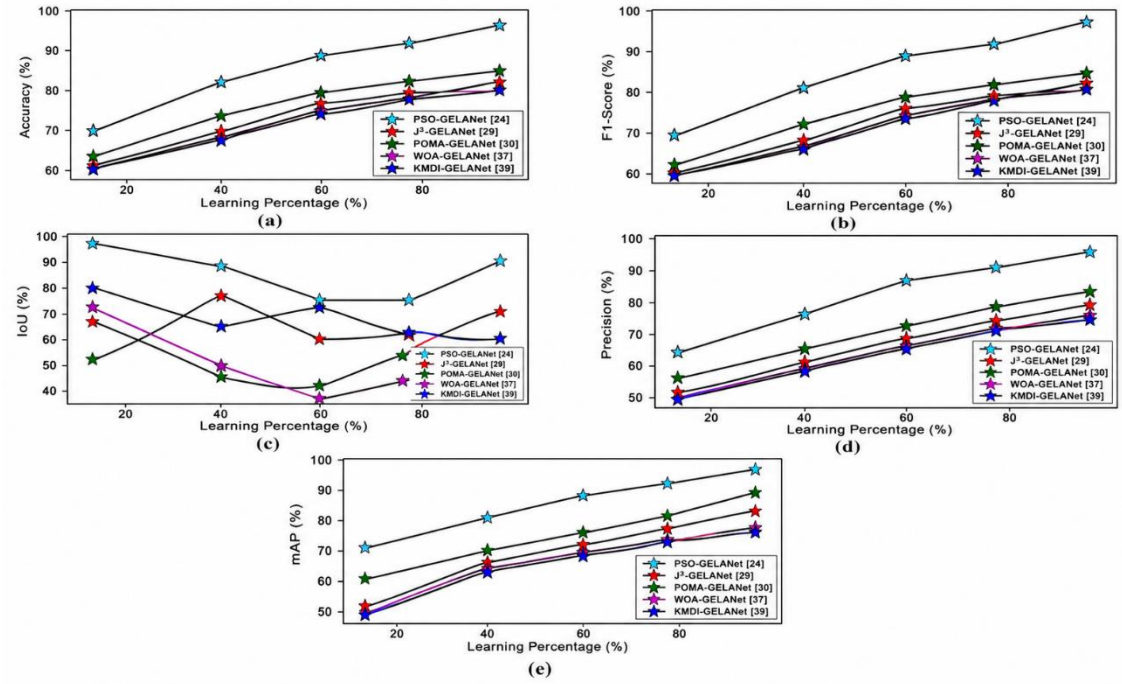


Figure 5. Performance Comparison between the Proposed Model and Benchmark.

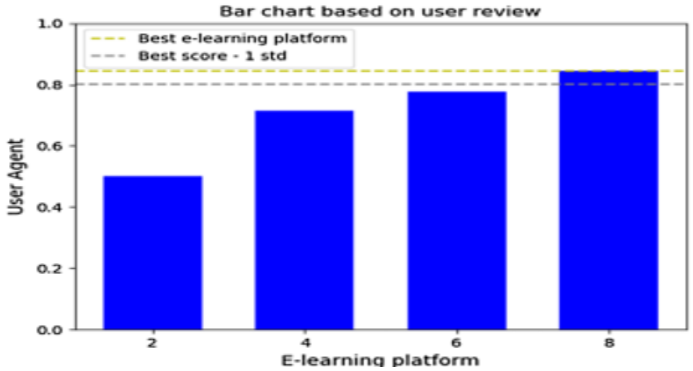


Figure: 6 User Review Graph.

Deep E-Learning Recommend Net (DELRNet):

The adaptive cat and mouse optimizer (ACMO) and hyper parameter tuning for RNN, automatic code, TF IDF, glove bed ending, and function weighting are all Subha et al. (2023). Your method was tested with data records with World Peace University, which had 20 courses and over 2,000 students. It was compared with many basic recommendations, including the PSO, Jaya, WOA, and standard CMOs, as well as CNN, RNN models, and auto coders Delrnet surpassed all designs with substantial margins, including 12% increase in accuracy compared to comparable models and a noticeable buoyancy of F1 scores and NDCG. Achieves amazing accuracy of 92.79%, 71.90% accuracy, 93.14% recall, 81.15% F1 score, 86.01% NDCG. These findings show that deep learning and meta-statistic optimization work together to provide accurate and relevant e-learning recommendations. Figure 7 illustrates the performance comparison of multiple deep learning models across varying learning percentages. In subfigures (a) through (e), it is evident that the proposed ACWO-DELNET consistently outperforms other models in terms of accuracy, F1-score, recall, precision, and MCC metrics. Performance trends indicate that increasing the learning percentage contributes to steady improvements for all models, although some exhibit fluctuations in certain metrics, particularly MCC. The results highlight the robustness of ACWO-DELNET, demonstrating superior stability and higher effectiveness compared to PSO-DELNET, JSO-DELNET,

WOA-DELNET, and CGO-DELNET. These observations emphasize the potential of hybrid optimization techniques in enhancing sentiment classification tasks across diverse datasets.

Fair Benchmark Comparison:

The performance of the proposed framework is compared with the benchmark results reported in the existing literature to obtain a fair comparison. The proposed framework outperformed the EELR and DELRNet under their respective experimental conditions, Figure 7, with an F1-score of 0.57 and an accuracy of around 57%. DELRNet, for example, reported an accuracy of 92.79%, recall of 93.14%, F1-score of 81.15%, and NDCG of 86.01%. These values are only indicative of better performance and should not be interpreted as a controlled head-to-head experiment since the benchmark models were not reimplemented and tested under the same setting as the proposed framework, in terms of data, preprocessing, train–test split, and hardware. As such the benchmark results are provided as a reference to the context of the school rather than as an indicator of statistical superiority. To fairly compare the two algorithms, the same datasets, preprocessing method, data partitions, hyperparameter selection method and evaluation method must be applied to both.

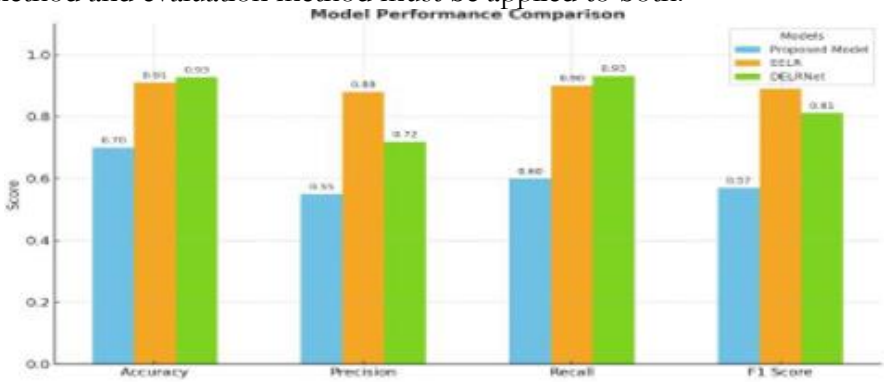


Figure 7. Model Performance Comparison.

Reasons for Lower Performance:

The proposed framework achieved lower performance than the benchmark methods considered in this study. This difference can be attributed to several technical factors. First, the proposed framework was evaluated using a relatively limited experimental setting, which restricts the amount of learner–resource interaction information available for learning robust recommendation patterns. In contrast, the benchmark approaches were developed and evaluated using larger-scale experimental settings, providing greater opportunity to learn complex learner preferences and interaction patterns. Second, the proposed framework combines learner profiling, NLP-based processing, collaborative filtering, and an intelligent assistant within a lightweight recommendation pipeline. Although this integrated design improves interpretability and supports practical learner interaction, it may not capture the deeper nonlinear relationships that can be learned by more complex hybrid deep-learning architectures. Third, recommendation performance can vary considerably across learners because individual learners have different interaction histories, preferences, and learning behaviors. This variation is reflected in the learner-wise evaluation results, where recommendation effectiveness is not uniform across all learners. Finally, differences in preprocessing, feature representation, model architecture, optimization procedures, and experimental data partitions can also contribute to performance differences between the proposed framework and previously reported benchmark models. Therefore, the lower performance should be interpreted in the context of the experimental conditions rather than as evidence that the overall framework is ineffective. The results instead highlight the need for

larger and more diverse datasets, stronger representation learning, systematic hyper parameter optimization, and controlled benchmark experiments in future work.

Computational Complexity, Scalability, and Inference Time:

The computational characteristics of the proposed recommendation framework are important for its deployment in large-scale e-learning environments. The framework integrates learner profiling, NLP-based processing, collaborative filtering, and an intelligent assistant, and therefore its computational cost depends on the number of learners, learning resources, learner–resource interactions, and the complexity of the NLP processing stage. Learner profiling and similarity-based recommendation require processing learner attributes and interaction information, while NLP operations introduce additional computational overhead when processing textual feedback and learning-resource descriptions. As the number of learners and resources increases, the interaction and similarity computations may become more expensive and may require efficient indexing, caching, and incremental updating strategies. The framework can be scaled by maintaining learner profiles incrementally, pre-computing resource representations and similarity scores, and updating recommendations only when new learner interactions become available. These strategies can reduce repeated computation and support deployment in larger learning environments. However, an exact inference-time and computational-complexity benchmark was not available in the retained experimental records; therefore, specific execution-time values are not reported. Future evaluation should measure training time, average recommendation inference time per learner, memory consumption, and computational cost under progressively increasing numbers of learners, resources, and interactions to establish the practical scalability of the framework.

Practical Limitations:

The proposed recommendation framework has several practical limitations that should be considered when deploying it in real-world e-learning environments. First, the framework may experience a cold-start problem when a new learner has little or no interaction history. In such cases, limited behavioral information can make it difficult to generate highly personalized recommendations. Second, sparse learner–resource interactions may reduce the effectiveness of collaborative filtering because reliable similarity patterns require sufficient interaction information. Third, learner diversity presents an additional challenge because learners may differ substantially in their interests, prior knowledge, learning preferences, and interaction behaviors. A recommendation strategy that performs well for one learner may therefore be less effective for another. Finally, real-world deployment introduces additional challenges, including continuous collection and updating of learner profiles, integration with existing learning management systems, privacy and data-management requirements, and maintaining recommendation quality as learning resources and learner populations change over time. These limitations indicate that practical deployment would benefit from incremental profile updating, hybrid handling of new learners and sparse interactions, and continuous evaluation using real-world learner feedback. Future work should validate the framework in larger and more diverse e-learning environments to assess its robustness under these practical conditions.

Conclusion:

This paper proposed a conceptual model of a recommendation system in e-learning with the aid of hybrid deep learning algorithms to counter the issue of information overload within the online learning context. The suggested system combines profiling and NLP-powered key-word extraction, intelligent assistants and feedback systems to produce personalized learning suggestions. Experimental testing through a confusion matrix and ROC analysis showed that the system has a basic capability to classify, but at the same time the performance of the system is not as good as compared to other advanced benchmark systems like EELR and DELRNet. The low F1-score and AUC indicate that further refinements were

required on the process of feature extraction, learner profiling, and optimisation strategies. On the whole, the results indicate that the suggested model offers a valuable platform of creating individualized e-learning systems, yet in further applications, the inclusion of more advanced hybrid optimization methods, more comprehensive datasets, and feedback loops could have a major impact on the model accuracy, its strength, and applicability in practice.

Acknowledgement: Acknowledgements are considered necessary.

Conflict of interest: There is no conflict of interest among all authors.

Project details: This research was not supported by any funded project.

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