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PAPER

Dynamic Pedagogical Resource Recommendation System for Students Using Rising Star Ranking Algorithm

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ABSTRACT

With the advancement of technology and the rapid growth of digital and electronic devices, the e-learning process has become easy and flexible. However, due to the lack of relevant and contextually linked learning resources, a problem may arise for students in their academics compared to physical learning, where the teacher is responsible for providing learning resources. Not only this, but there exist many other problems, like the privacy of course contents, and less availability of relevant learning material has also been responsible for the low assessment scores of students. In all situations, a need exists to provide quick, relevant, and user-friendly accessible content to the students at their doorsteps. In this study, a machine-learning technique has been designed to recommend relevant content in an e-learning environment. This work utilizes innovative machine learning-based adaptive course content to strengthen 'students' capabilities. The proposed method consists of data preprocessing, feature extraction through VISUWORDS, feature reduction through formal concept analysis (FCA), and finally, ranked material using the Rising Star algorithm. The experimental evaluation shows that the proposed technique offers a better turnout in accuracy (87%) than the existing benchmark methods. Last but not least, the proposed technique has also been analyzed to validate student performance through pre-posttests that show the remarkable performance of the f-score.

KEYWORDS

machine learning, recommendation system, e-learning, course recommendation systems

1 INTRODUCTION

Due to modern information and communication technology, e-learning supports a broader range of knowledge and skills than conventional education and is not constrained by physical location or time [1]. The e-learning platform increases students' events of learning at their own pace, and teachers advance in their careers by enhancing their academic and technical abilities [2]. While there are numerous advantages to e-learning, there are also some disadvantages [3], [4]. For example,

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there is insufficient assistance and advice for e-learning, inadequate guidance in content selections for individual requirements, etc. In many disciplines, contextual knowledge is efficiently used to produce essential suggestions [5]. To provide more valuable suggestions, addressing such issues as too much information, data redundancy, and context redundancy is crucial.

The recommendation system generates recommendations by taking user interest into considering user interests and using contextual data [1], [6]. Customized choices help learners by suggesting particular content improvements to their learning experiences. Current e-learning research focuses on creating recommendation procedures that are projected to perform better than the current recommendation approaches [7].

There are many existing recommender systems: collaborative filtering, content-aware filtering, hybrid filtering, deep factorization machine, knowledge base recommender systems, and neural collaborative filtering [8], [9]. Existing e-learning platforms such as massive open online courses (MOOCs) [10], Coursera [11], and existing recommender systems need to enhance the learning process and optimize the teaching process [12]. Therefore, our study offers the content recommender system to students and teachers using the Rising Star algorithm. It is a novel approach in the machine learning (ML) environment to achieve personalized content. In customized content, generation provides complete learning process guidance. They are contributing to the e-learning platform so students can understand the content efficiently. The proposed method was executed on an openly available data set from the Massachusetts Institute of Technology (MIT), UAAR, and miscellaneous websites such as CNX (Sharing Knowledge and Building Communities—OpenStax CNX, 2020).

In this study, we presented the design implementation and application of learning management system (LMS)-ranked content using ML for predicting 'students' performance in computer science. To enhance recommendation quality, metadata, such as a 'course's content information, has usually been utilized as extra knowledge. Using text mining for semantic analysis of courses' data, an information system has been created to improve trainer mentoring and student performance [14], [15]. An evaluation parameter of a confusion matrix was used to assess the effectiveness of our recommender system, and the empirical results highlight the present work's originality.

The general structure of usage of an e-learning environment where an instructor guides the students through online course materials is explained in Figure 1. In this environment, an LMS has been designed that facilitates both students and instructors. The use of a data analytics tool [16], [17] in combination with an LMS is critical for improving teaching quality and course design. Given the background of student performance analysis on online courses, the following points will be examined in this paper:

Are the existing state-of-the-art e-learning systems in the literature providing adequate learning material recommendation engines to enhance student performance and academic achievements?

"How can the implementation of essential measures facilitate the establishment of an effective e-learning recommendation environment aimed at enhancing student learning outcomes?

What are the performance parameters required for predicting student performance in e-learning recommendation system evaluation?

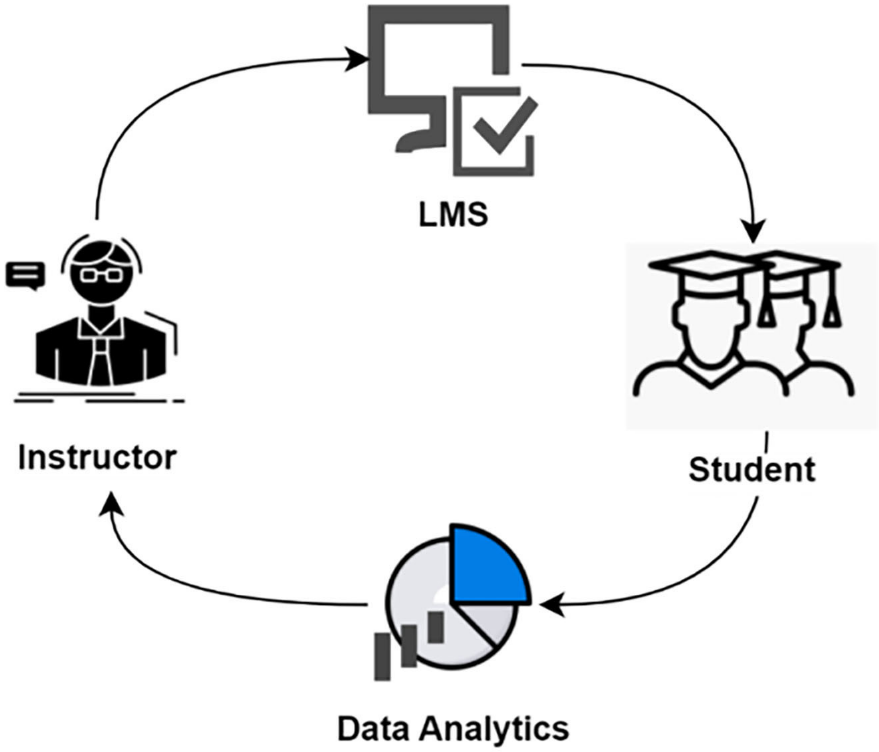


Fig. 1. Effective usage of e-learning

Predicting student performance in e-learning is challenging and known as knowledge tracing [18]. Knowledge tracing monitors a student's learning progress by analyzing online engagement to assess cognitive proficiency and mastery of skills. Existing methods use knowledge tracing to predict learners' needs and provide suggestions based on their knowledge levels. This involves training metrics for performance prediction and student dropout models. Their work offers guidelines for model implementation and analysis, exploring concepts such as collaborative filtering, Bayesian networks, and association rules. However, their system may not encompass the entire learning mechanism and dimension.

In this study effort, an ML based approach is utilized to increase student interest and engagement in the course by applying ML-based algorithms and techniques. One of the significant challenges in many information retrieval (IR) applications is ranking. In the discipline of IR, several ML techniques with diverse ranking applications have added new aspects. For this, we proposed a framework to provide students with machine learning-based ranked content using a Rising Star algorithm to enhance their performance in the course.

Machine learning algorithms in this study predict students' output in development so that educative steps can be taken. The datasets will be used in this analysis function as inputs for training and evaluating ML algorithms in this way. The student output for the chosen course session can be calculated using the model generated with the computer science course results. This prediction can help learners, students, and teachers [1], [19]. The main contribution of this study is given as follows.

To investigate the existing literature to understand the current predictive models for learners' academic achievement, which improve the learning process with a suggested recommendation engine and efficiently allow access to the relevant and interactive learning material.

To provide a user-friendly environment and straightforward access to multiple disciplines' learning materials.

Enable students to improve learning material recommendation and student performance by providing pre and post-test comparisons to get a better outcome.

The remaining paper is divided into following sections: Section 2 presents a Literature Review. Section 3 shows the proposed model preliminaries, including VISUWORD and formal concept analysis (FCA) methods. Section 4 describes a methodology after that section 5 presents the experimental setup and evaluations which further illustrate the method of the experiment and data set. Finally, the conclusions and future work are presented in Section 6.

2 LITERATURE REVIEW

Research and the practical use of technologically enhanced learning (TEL) in education have sparked a significant discussion concerning the use of technology in education, specifically the use of TEL. As a result, in this part, we describe the literature on customized recommendation systems and ML-based e-learning solutions and analyze how other recommender systems compare to ours in terms of how well students learn. To further compare our method, we present this section by outlining how recommendations of learning materials from other recommender systems are offered in the literature. Students' performance in e-learning can be a fundamental and necessary measure of the quality of the learning experience and its outcomes [20]. The e-learning construct covers a wide range of applications, learning strategies, processes, and areas of academics. Besides the conventional demand, it has become the most desirable environment during the COVID-19 pandemic. Clark has discussed the analysis and evaluation of remote teaching methods for students' academic results is critical, particularly during a severe pandemic such as COVID-19 [21].

E-learning has many algorithms, some are ML-based, AI-based, and sentimental analysis-based. Algorithms and techniques are applied at graduate and post-graduate levels, which utilize LMS, an online course designer application. In this section, some core techniques are discussed for predicting student learning performance using AI techniques [4]. This section will also cover limitations, proposed methodology, and data collection of each state of art related intelligent e-learning system. At the end of this section, we will be able to conclude the research gaps in existing models of the existing e-learning-based student prediction models.

The lack of student engagement in different course activities and diverse course materials is one of the most critical difficulties connected with e-learning systems discussed in 'Hussain's research [22]. To examine the influence of engagement on academic achievement, Hussain utilized ML algorithms to detect low-engagement participants in a social science subject at the Open University. Hussain used various ML algorithms on the datasets to predict low-engagement individuals. These methods were used to create training models that were then compared regarding f-score measure and kappa values. The findings showed that the J48, decision tree, JRIP, and gradient-boosted classifiers performed better than the other evaluated models regarding accuracy, recall, and kappa value. Hussain created a dashboard to help instructors at the OU based on our results. In addition, the link between student involvement and course evaluation scores was investigated in this study.

The development of an excellent learning style model that captures the student's characteristics was based on implementing the demand for an efficient e-learning system. Among those qualities is the learning style, which refers to a student's desire to study [23]. Aissaoui presented a method for automatically identifying a learner's learning style based on prior actions and employing web resource mining techniques and ML algorithms. Internet use mining techniques were employed to pre-process the log file compiled from the E-learning environment and record the learners' activities. The sequences of the registered learners were sent into the K-modes clustering algorithm, which grouped them into 16 learning style combinations. The naive Bayes classifier was then used to predict a student learns differently in real time. To test the Aissaoui method, a real dataset taken from an e-learning system's file system, as well as the confusion matrix method, has been used to assess the classifier's effectiveness.

Khanal presented an overview of recommendation systems in the e-learning environment in this paper, dividing them into four categories: content-based, collaborative filtering, knowledge-based, and hybrid systems [24]. Khanal created a taxonomy that includes all the elements needed to develop an effective recommendation system. ML approaches, algorithms, datasets, assessment, valuation, and output were discovered to be essential components. Their work contributes significantly to the area by giving a much-needed summary of current research and lingering problems.

Fareeha [25] used investigations to explain learning styles in both online and offline contexts. In their investigation, the authors uncovered new attributes and scaled down previously reported attributes to better determine the learner's learning style. The authors applied classification methods to the dataset and compared their accuracy. Various fascinating patterns in learner behavior were noticed as they learned different types of concepts in different contexts.

Alshabandar [26] explained that high-ranking colleges have used MOOCs as an efficient dashboard platform via which students from all over the world can engage in such courses. Their research presented two predictive models: students' assessment grades and final student performance. The models were used to identify the elements influencing students' learning achievement in MOOCs. The results demonstrated that both models produced feasible and accurate outcomes.

Maksud and Ahmad worked on academic learning prediction performance, which is a problem for educationally relevant persons such as administrators, instructors, students, parents, and others [27]. Because poor learning performance can lead to a student's failure, it's critical to forecast performance to identify students who are at risk. By identifying the learner at risk, immediate measures for improving performance can be taken in advance. This study aimed to identify students who may have difficulties in the upcoming class sessions. Maksud performed a comparative analysis of the collected characteristics for the following ML algorithms: Naive Bayes (NB), logistic regression (LR), artificial neural network (ANN), support vector machine (SVM), and decision tree (DT). The results showed that SVM outperforms other ML approaches in performance prediction, with an accuracy of 94.82 percent. Table 1 presents an overview of different ML-based approaches used in e-learning platforms.

Table 1. Literature review of e-learning ML-based performance

Ref. No.	Design Approach	Evaluation Factors	Algorithm Used	Tool Used
[28]	Prediction model	Precision, Recall, and F-measure	Random forest algorithm	WEKA MATLAB
[29]	Predictive Model	Accuracy and Recall,	J48, Decision Tree, and Gradient	RapidMiner tool
[22]	Exploratory Data Analysis	K-means method	Dimension Reduction Model	Python
[23]	Customized approach	Classifier and confusion matrix	K-modes clustering	FSLSM dimensions
[30]	Artificial Neural Network	Precision and Recall	Optimization algorithm	Natural Language Tool Kit
[31]	Mixed Method Approach	Multiple Linear Regression	Social network analysis, K mean Clustering	Python "sklearn" toolkit
[32]	Hybrid technique	Confusion Matrix, F-score	Content-aware filtering	Matlab
[27]	ML approaches	Logistic Regression	Artificial Neural Network (ANN), Naïve Bayes (NB)	WEKA
[33]	Point-wise and pair-wise approach	Mean Reciprocal Rank	Learning to Rank	Python

Panagiotakopoulos [34] emphasized the vast volumes of data being collected and maintained in institutional repositories regularly on students' demographic traits, activity patterns, and learning performances. Their research used various cutting-edge supervised ML techniques to predict student dropout in a MOOC for experts at an early stage. Based on data obtained during the first week of the course, the trial findings demonstrated that accuracy exceeds 96%, allowing for effective intervention tactics and support measures.

Another study has attempted to develop a system that analyzes learners' behavior using data gathered on the Moodle LMS online learning platform and uses the Linear Regression method to predict the learning average score at the end of the student's course [35]. The study aimed to give lecturers criteria for categorizing student learning outcomes early on in the teaching process. Based on this information, the instructor can identify students in danger of failing the subject and alert them to the need to modify their study habits more actively to obtain adequate results. As a result, the number of students falling and dropping out of school was reduced after the course.

The majority of the research focuses on various techniques for increasing the efficiency of the IR retrieval [36]. Learning to rank is a popular ranking mechanism that employs an ML method to arrange documents of various categories in a specific order based on their ranking in literature.

Based on the above discussion, it has been observed that most of the existing educational resource recommendation systems are based on semantic models of tagging and user-based filtering. Although remarkable, they cannot deliver automated ranked content to students. Moreover, all such methods are time-consuming and complex recommendation systems regarding utilization and diverse learning materials. As far as the ranking of educational resources is concerned, it keeps evolving as per the requirements of learners. The proposed framework provides an efficient resource recommendation technique that will help to learn without the hussle of searching on multiple platforms.

3 MATERIAL AND METHODS

This section provides the descriptive core concepts and models used in this proposed work. The core models from ML and AI have been utilized. For contextual linking of concepts of datasets are connected with the help of the existing online tool VISUWORDS [37]. To derive rules from existing concepts, FCA is used [38]. The ranking of relevant course contents is achieved through the rising star algorithm. The details of each technique are presented here:

3.1 VISUWORDS

A visual dictionary allows look up words and learn about their origins and similarities with other terms and words. It produces nodes with all of the related terms and the meaning and every aspect of the phrase. The user can tap a node to see a definition for that word category and press and drag individual nodes to help explain connections. Figure 2 shows a synset is a series of words or synonyms that describe a single definition. VISUWORD enables users to look up words to find their definitions and connections with other terms and concepts, consistent with exploring relational chains. VISUWORDS shows how closely words are associated and what kind of interaction occurs between them. The result is a network diagram that connects the main word to other terms and concepts.

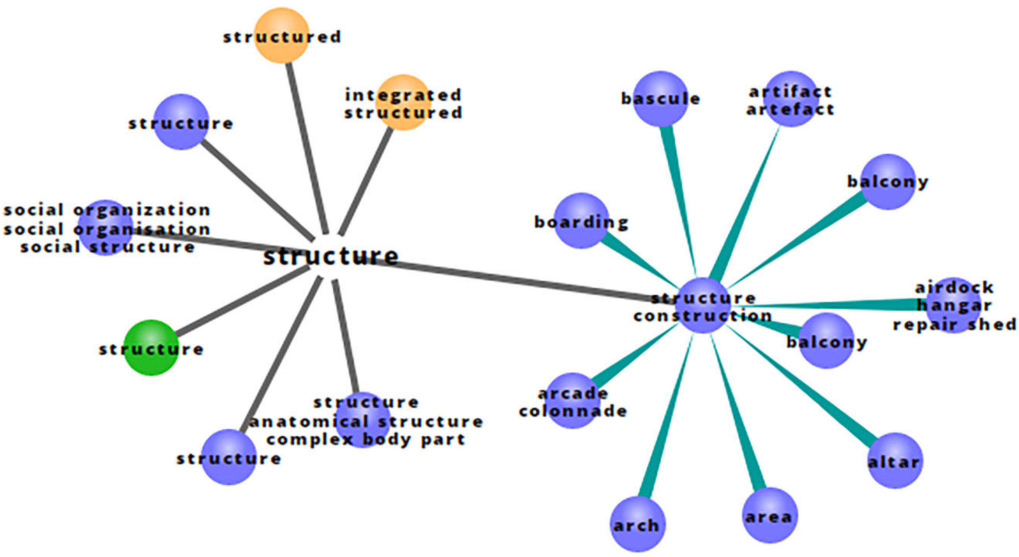


Fig. 2. VISUWORDS visual representations

3.2 Formal concept analysis

Formal concept analysis is focused on concepts and logical hierarchy. It stimulates mathematical thought to study conceptual evidence and explore new knowledge [39]. Supervised classification based on FCA includes creating classifiers (functions or models) from details to forecast classes for potential data. It aims to derive rules from data based on earlier generated principles. Concept lattices may define the relationship between objects and attributes as the primary data structure in structured concept analysis. A formal context in FCA is typically defined as a Boolean matrix, with rows (objects) and columns (attributes) comprising only 1s and 0s, from which the definition of the lattice can be deduced.

4 PROPOSED METHOD

This section provides a complete discussion of the proposed methodology based on preprocessing, feature extraction, feature reduction, classification, conceptual mapping, ranking, and final recommendation. The structure of the proposed approach is shown in Figure 3, which indicates the different steps of the proposed approach. The data collection was done precisely from selected sources for graduate programs and selected courses. Once the dataset is collected, the proposed model takes it to the preprocessing of dataset documents using NLP techniques. As discussed earlier, VISUWORD and FCA are used for contextual linking of concepts in given datasets. The rising star algorithm ranks the given concept as per the relevancy of relevant documents for students and redirects it to the content recommendation system. Last but not least, validation is conducted to assess the proposed approach's effectiveness.

4.1 Preprocessing

Initially, the documents are converted into word counts. The second operation is used to remove empty sequences, which includes cleaning and filtering textual learning resources [40]. Through Algorithm 1, it is clear that preprocessed learning resources are split into textual units using different steps. After that, some of the features are eliminated to remove uncertainty and repetitions that reduce the proposed work's complexity. The final feature list is generated using the NLTK library to get the most semantically significant features. Algorithm 1 provides the programming-based description of preprocessing.

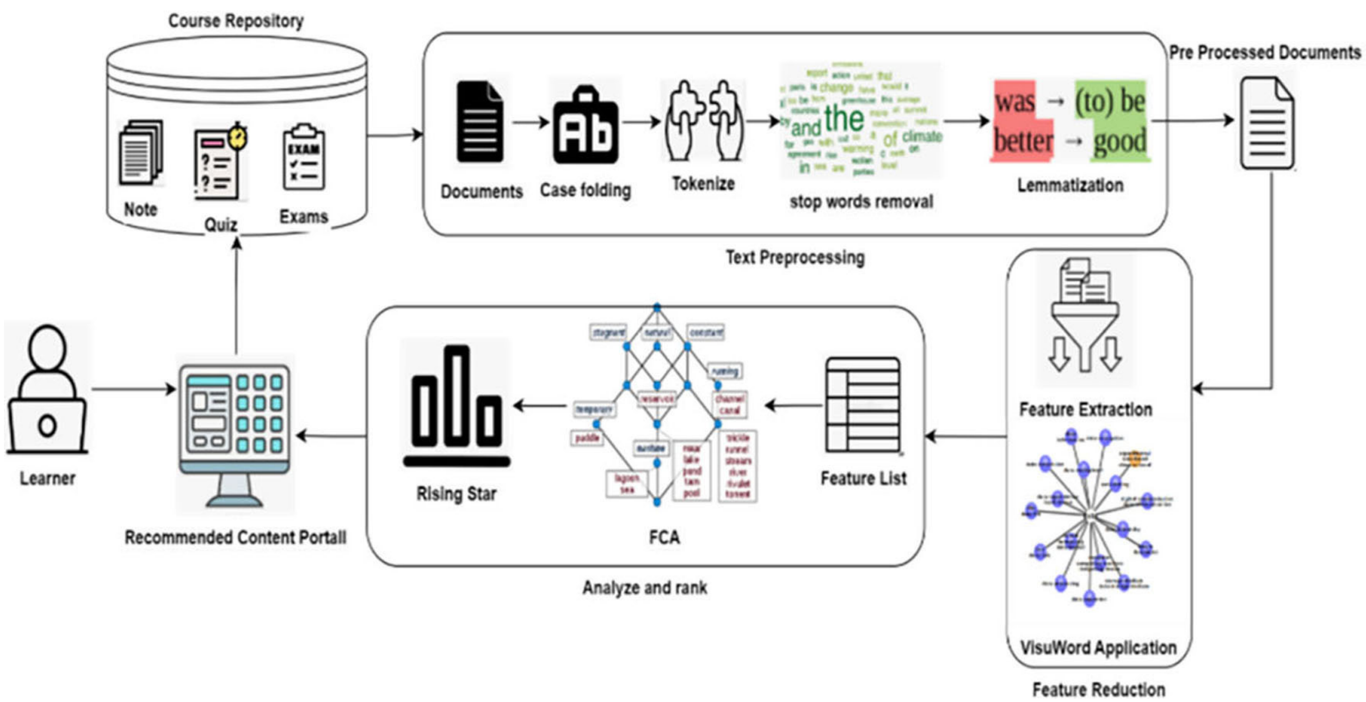


Fig. 3. Proposed model for e-learning platform

Algorithm 1: Pre-Processing of Learning Resources

```
Input: Set of documents (ID)
Output: Preprocessed Words (Pw)
START
1   Initialize Pw←∅
2     For all I ∈ ID
3         String F is a list of tokens after case folding
4                 End of ID
5           Tokenization (ID)
6           Casefolding (F)
      End for
7     For all FD∈ F
            Stopword Removal (SR)
8           (SR) ←Lemmatizing
      End for
9   Return Pw
STOP

Functions
1   Tokenization (I)
      For all I in ID
        Convert terms into tokens T
      End for
        Return T
2   Casefolding (T)
      For all fD Tokens T
        Lowercase' 'words' (T)
      End for
        Return (F)
4   Stopword (F)
        SR = remove(ed, ing, as, if, the)
      For all LD
        lemmatizing (SR)
      End for
        Return (L)
```

4.2 Feature extraction

After the data is preprocessed and a draft list of candidate features is obtained, the next step is to extract features using VISUWORD (https://visuwords.com/). For instance, if a student searches for a topic related to their course, VISUWORD displays all the information related to the topic.

The visual representation of functions is shown in Figures 4–6, where distinct colors—blue denoting nouns, green denoting verbs, red denoting adverbs, and orange denoting adjectives—are employed. The synsets are interconnected through color-coded chains, delineating their specific relational dynamics. Upon entering any term into the search bar, a network comprising nodes, or synsets, will be generated, constituting the resulting network of interconnected nodes.

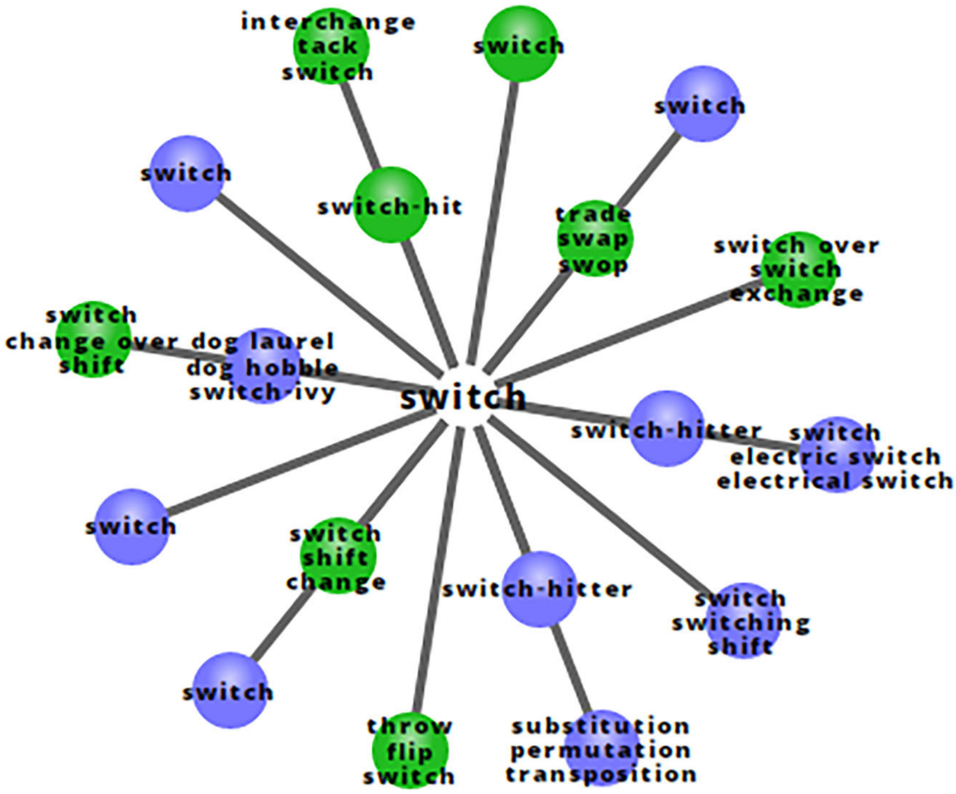


Fig. 4. Term switch with its synsets

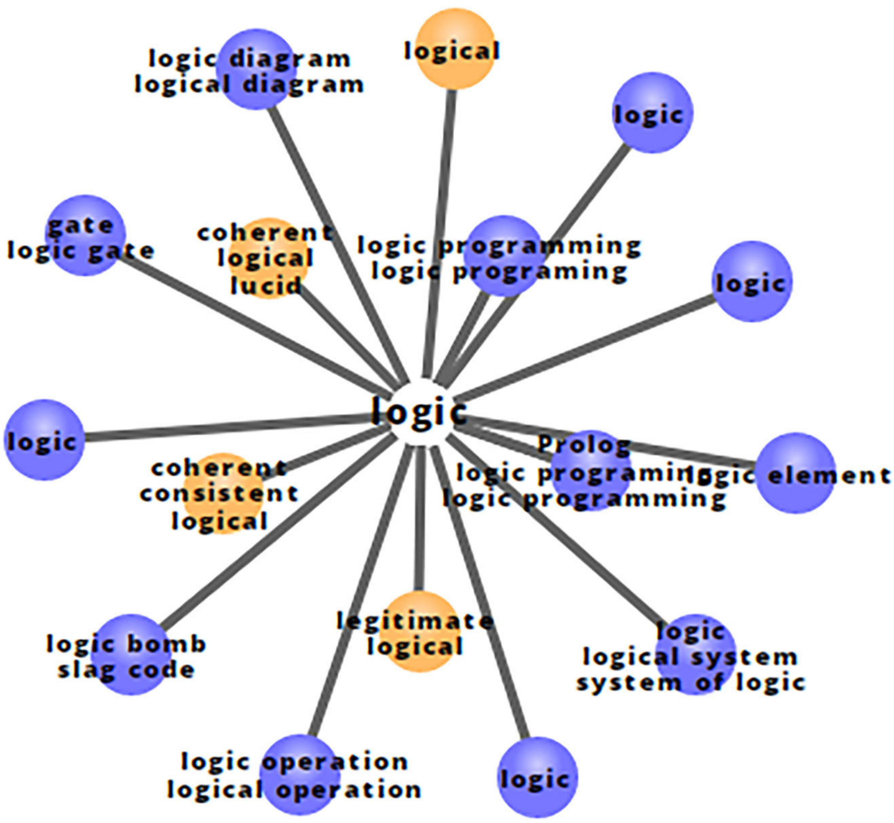


Fig. 5. Term logic with its synsets

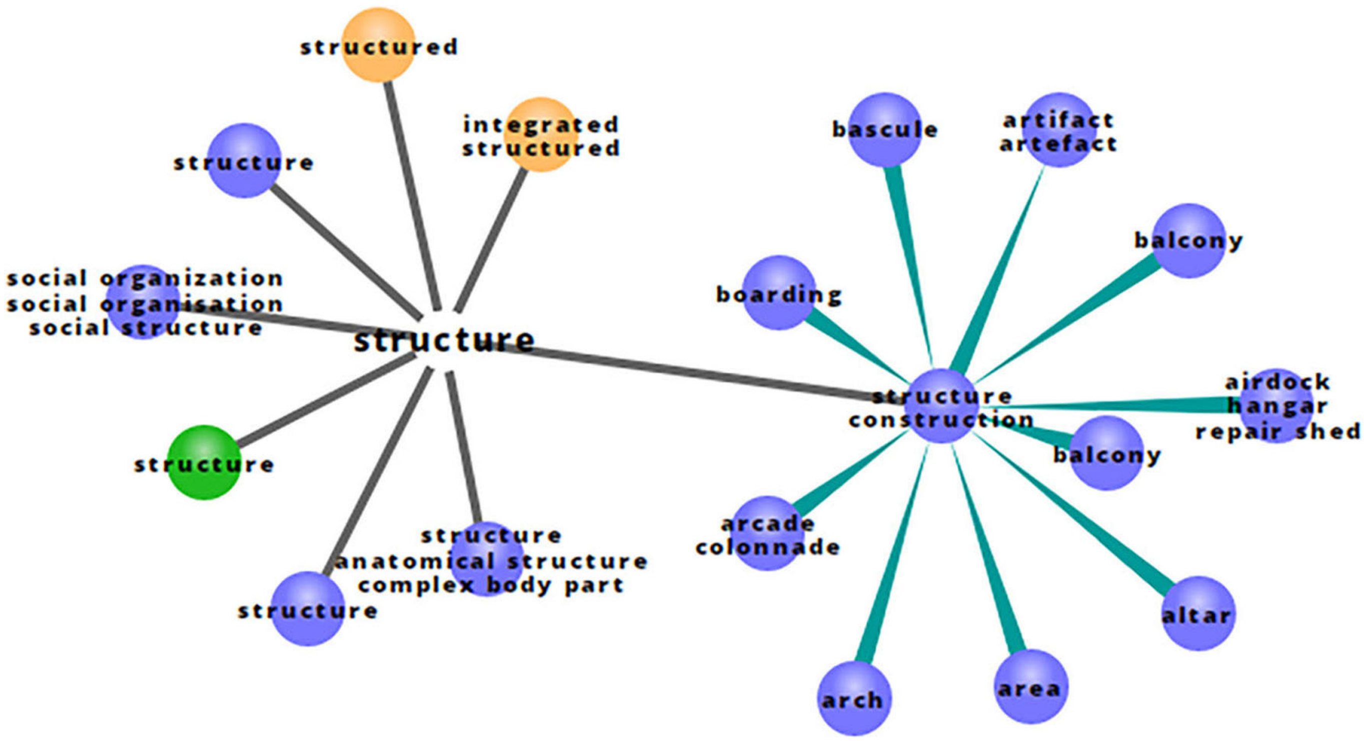


Fig. 6. Term structure with its synsets

4.3 Feature reduction

To reduce the complexity of VISUWORD data, it would be analyzed using FCA by making different attributes and conceptual mapping. Figure 7 shows the terms in different classifications. To find knowledge about the computer, one needs to extract some information about these objects, which requires various methods of data analysis scientifically. When working with vast amounts of data, the issue of data representation is apparent—focused on one such type of data analysis of students' results using the concept of FCA.

Finally, after feature reduction, an auto-pruning based on reinforcement learning is performed to obtain optimal features. The pruned data is transferred for ranking using the rising star algorithm. The Rising Star algorithm generates interpretable feature significance rankings, allowing users to choose the most essential features in the categorization process. The Rising Star Algorithm pruned data to be transferred, and based on this algorithm, it would do a ranking of course material based on content. With the aid of the rising star algorithm, it automatically estimates the number of important characteristics and the model's complexity, making it suitable for a wide range of datasets. The top document features have been selected for recommendation to students.

A many-valued context (G, M, W, I) is made up of a set of G, M, and W as well as a ternary relation I between G, M and W (*i.e.*, I, G, M, W) that maintains as per Equation 1.

$$((g, m, w) \in I \; and \; (g, m, v) \in I)N = U_{m \in M} \tag{1}$$

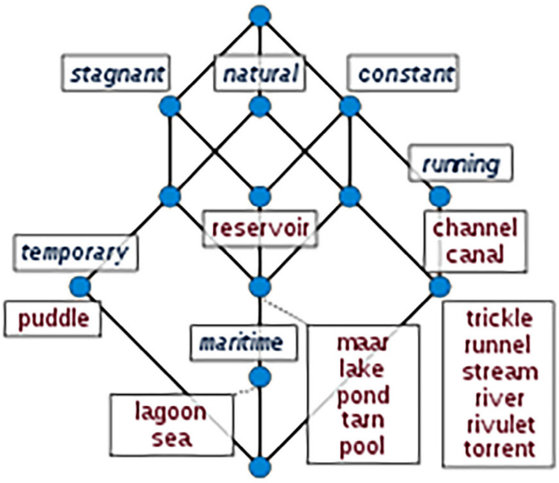


Fig. 7. Feature reduction through formal concept analysis

4.4 Final recommendation

The final recommendation of learning content is made possible through the rising star algorithm. In the rising star algorithm, a given d document with features is considered. For example, (ID1, y1), (ID2, y2) … (IDn, yn), where n is the total number of documents. IDi is feature of words wi where IDi∈Rm, m is the total number of features, and yi∈{–1, +1}. To identify if the document words or files are ranked or not, the prediction function is defined.

$$y = FRS(W/I) \tag{2}$$

Where

$$FRS(w/I) = [>= 0 \text{ } if\ y = +1, \text{ ranked document}]$$

$$FRS(w/I) = [< 0 \text{ } if\ y = -1, \text{ not ranked document}]$$

The working of the rising star algorithm is explained in Algorithm 2. The final output of the proposed model is a list of semantically relevant recommended learning resources that indicate the student requirement. When the students access the proposed system portal, they receive learning resources per their needs. This valuable output not only increases 'students' knowledge but also helps in improving student's performance.

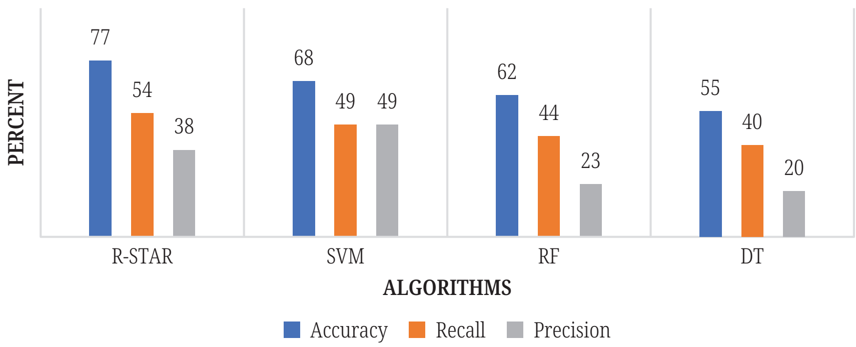


Fig. 8. Comparison of performance of the proposed model with state of art techniques

Algorithm 2: Rising Star Algorithm

```
Input: Dataset (document set) and parameters
Output: Ranked Documents
START:
    For all I
        FRS(w/I)=[>=0 if y=+1]
        FRS(w/I)=[<0 if y=–1]
    End For
        Return not ranked document
STOP
```

After the recommended content generator for students performed validation of two groups, one group with proposed training and other with traditional training. We have compared the result of the rising star algorithm with other performance algorithms: SVM, decision tree, and rising star algorithm.

Figure 8 depicts the experiment results and compares the decision tree, SVM, and rising star with evaluation parameters of precision, Recall, and F score measure. Data with the rising star algorithm result in 60% precision, 70% recall, and 80% F-measure which is high compared to other algorithms.

Concluding the discussion, the proposed FCA-based ranking model is promising in providing semantically relevant learning content to students. The suggested model is intended to deal with high-dimensional data effectively. It can handle datasets with many characteristics, which classic ML methods like random forest and SVM find difficult. The rising star algorithm may filter out unnecessary or noisy features, lowering the influence of irrelevant information on the classification process and boosting Recall. The suggested model includes an adaptive learning mechanism that modifies the model's complexity in response to the dataset. Different levels of academics can be catered to through this model. The text preprocessing is based on NLTK, an encouraging library.

Furthermore, VISUWORD has enabled auto-mapping of semantically related words (features). Moreover, the FCA base concept lattice is beneficial in reducing the complexity of the proposed model. Finally, the learner receives a recommended list which is ranked based on semantic significance and related to 'students' performance parameters discussed in further sections. The suggested FCA-based ranking methodology efficiently delivers educational content that is semantically meaningful, supports high-dimensional data, and adjusts to various academic levels. The model's accuracy and applicability are increased by using NLTK for text preprocessing and VISUWORD for auto-mapping. This helps educators create curricula and greatly improves the tailored learning experiences for students.

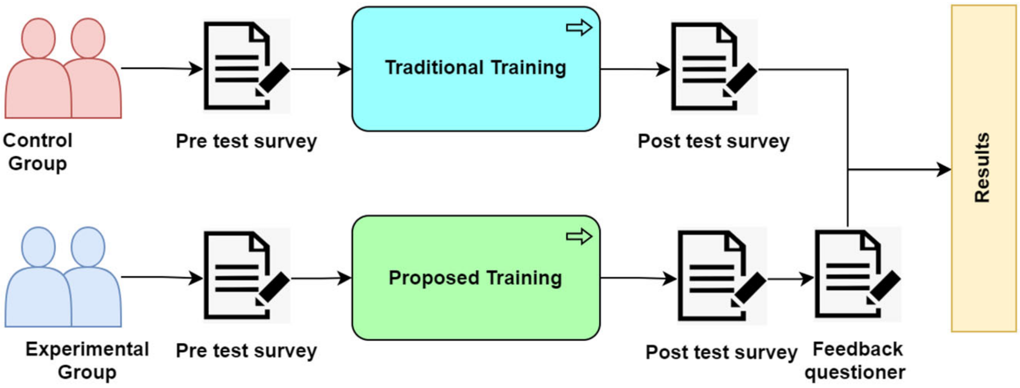


Fig. 9. Experimental flow for proposed model evaluation

5 EXPERIMENTAL SETUP AND EVALUATION

A user-friendly web-based application was used for empirical evaluation of the proposed framework. The application was significant, as it transformed the proposed framework into action. It also provided functionalities for creating and revising a course. With the help of prototype-based assessment, the usefulness and effectiveness of the proposed system were evaluated, and results were analyzed. This section also explains the evaluation conducted through pre-test and post-test experiment techniques. The subjective assessment is performed through a 'learner's feedback survey adapted from [41].

5.1 Experimental process

Figure 9 shows the experimental flow conducted to evaluate the proposed model. The total number of participants for this experiment was 75. Two groups of students were created, namely the Control Group and the Experimental Group [42]. A larger experimental group was chosen in order to evaluate the efficacy of the suggested model with sufficient statistical analysis while keeping a reasonable control group for baseline comparison. Thirty individuals were assigned as controls and 45 as experimental participants. To ensure that the participants had comparable educational backgrounds and starting skill levels, they were selected based on their participation in a computer science degree program along with applicable courses ("Python, C++, Software Engineering") and lastly availability for comparative study.

Initially, 30 participants from the control group were selected. They were not provided with any specific training. They were assigned to a computer science degree program and a "Python," "C++," Software engineering" course. 45 participants were assigned a Software Engineering data set and put in the Experiment group. The Experiment Group was trained with our proposed learning model-based application. Experiment Group training included a computer science degree program and the "Python, C++, Software Engineering" course data set, including all modules with our recommended content for proposed training.

After the system's successful deployment, a detailed comparison with the existing benchmark methods has been provided at the end of this section. It has been concluded that the performance of the proposed work is far better in terms of F-measure, Precision, and recall. From this section, the obtained precision was 60%, Recall was 70%, and F1 was 80%.

To validate the usefulness of our proposed model, a pre-test survey was conducted for both groups. In this pre-test survey, both groups filled out MCQs based on questions related to the courses assigned to the groups, respectively. Their results were recorded for comparison. Afterward, the experiment was performed in which the control group used general internet searching using search engines of their choice. Whereas the experiment group used a mockup application based on the proposed model. Once the search task was concluded, a post-test survey was also performed for both groups. Both groups have taken test surveys based on MCQs, taken the course feedback, and then evaluated. Furthermore, the experiment group that used our proposed prototype, was also asked to give feedback to evaluate the recommended quality design and content relativity of retrieved learning resources.

5.2 Dataset

In this work, the data set of 1000 publicly available documents has been chosen from MIT, UAAR, and multiple web sources respectively (https://www.mit.edu [43]) (https://www.uaar.edu.pk (PMAS-Arid Agriculture University Rawalpindi, 2024)) (https://cnx.org [13]). The data set includes lectures, quizzes, assignments, midterm, and final exams.

Table 2 provides a comprehensive structure including the source, URL, number of documents, and vocabulary size of each data set for easy understanding. Most of the data from these sources have been obtained using a query-based search process. Due to the privacy constraints of universities, some of the data has also been accepted by public request. After the successful formation of the data set, it was split into training and testing sections of which 70% was trained and 30% was test set, respectively.

6 RESULTS AND DISCUSSION

After successfully conducting pre-test and post-test experiments with groups A and B, a feedback-based survey was conducted with the participants to evaluate the acceptance of the proposed system. A twelve-question questionnaire was created using the WebCT survey tool [45]. Participants were asked to complete the survey as part of their coursework, and the response rate for both groups was 100%. The survey's five questions were created to collect comprehensive feedback on critical aspects of integrated course design, content quality, and content relativity. The questionnaire included questions that probed for specific data, such as the amount of time students spend on tasks, in addition to more general traits, such as acceptance and contentment. Participants were encouraged to submit suggestions for changes in any aspect of the course design that was being reviewed, and they were given multiple opportunities to do so. In addition, questions on a participant's level of contentment with the performance of the recommended content or the efficacy of the e-learning network itself were included in the survey.

Table 2. Dataset size and vocabulary description

Source	Link	No. of Document	Vocabulary Size
Manchester Institute of Technology	Massachusetts Institute of Technology	300	7250
LMS (UAAR)	http://www.uaar.edu.pk/uiit/downloads.php?dept_id=31	200	3000
Miscellaneous (Web forum)	https://cnx.org/contents/-2RmHFs_@206.4:EVOE6JFo@4/Jb0105-Java-OOP-Similarities-and-Differences-between-Java-and-C	500	5668

Figure 10 summarizes the 'participants' feedback (mean value) broken down into parameters like course design, content quality, and relativity. The performance of the proposed model has been compared with different LMSs and is explained in Table 2. The difference in user satisfaction between the experimental and control groups, particularly in course relativity, quality, and design, suggests that the rising star algorithm and VISUWORD and FCA linking may improve results.

Course relevance, quality, and design satisfaction were 78%, 89%, and 86.4% higher in the experimental group, indicating the proposed system's success. In contrast, the control group's 33%, 41%, and 32.14% satisfaction ratings in these criteria show a significant difference in learning experience perception. The rising star algorithm helped the experimental group express 93% satisfaction in course relativity by accurately recommending courses or content that match student requirements and preferences. Users experienced the content as more relevant and applicable since the ranking method likely found and prioritized more relevant materials.

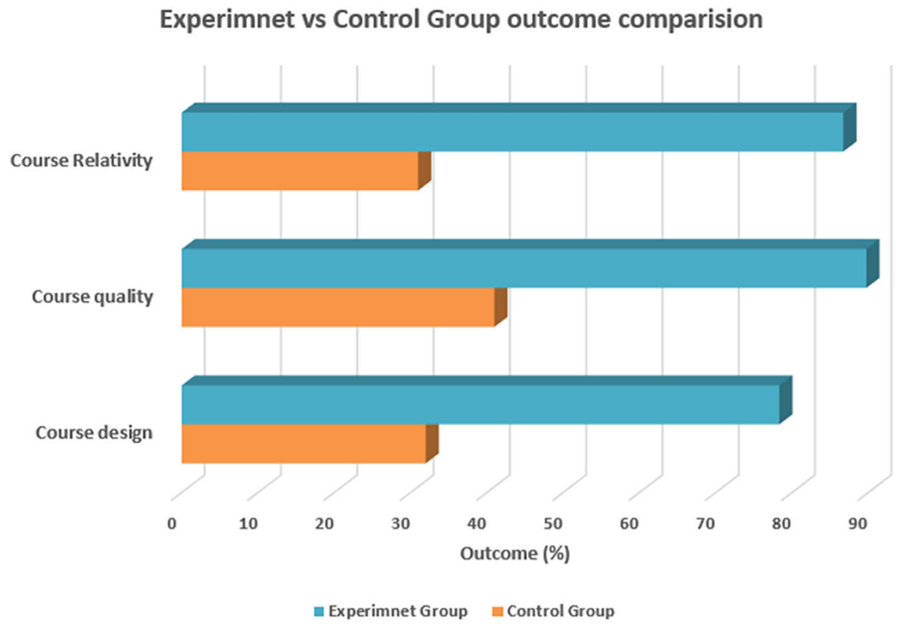


Fig. 10. Summary of the 'participants' feedback

Table 3. Feedback control and experiment group after experimental evaluation

Course Design (%)		Content Quality (%)		Content Relativity (%)	
Control Group	Experiment Group	Control Group	Experiment Group	Control Group	Experiment Group
33.45	78.34	41.76	89.76	32.14	86.74

As a result, a sample of 700 learning resources was used. These learning resources came from MIT & UAAR as well as various web resources. The fact that the selection criteria satisfied the requirement that was suggested for the model led to the choice of this particular collection of educational resources. In the same vein, Computer Science was selected as the only area of study to concentrate on to ensure that accurate comparisons can be made. Table 3 indicates that the experimental group's 78% quality parameter satisfaction rate may be due to Visuword and FCA helping the system filter and recommend high-quality resources. These linking methods certainly helped develop strong linkages between concepts and resources, ensuring high-quality and user-satisfactory recommendations. On course design, the experimental group's 89% satisfaction implies that the system's linking methods organized and presented the recommended information in a user-friendly manner. FCA may have helped structure the content hierarchy, providing an intuitive and well-organized interface and improving user satisfaction with the course design.

A lack of personalized recommendations and less refined content curation may explain the control group's lower satisfaction ratings across these dimensions, resulting in a perceived mismatch between user demands and offered materials. The experimental group's better user satisfaction rates may have been due to the effective integration of the Rising Star algorithm for ranking and VISUWORD and FCA for linking. These methods likely improved content relevancy, quality, and presentation, improving user satisfaction with recommended learning materials. This example demonstrates that the proposed solution is superior to the alternatives in terms of effectiveness. The proposed model has a feature where users can access course notes at a rate of 44%, which is a greater percentage than Moodle's (30%), learn's (20%), WebCT Vista (30%), and ECollege AU+ (20%). The constraints for accessing assignments in the proposed model are 56% more stringent than those in existing LMS. Then, the overall navigation throughout the site is compared to our suggested model, and the result is 49%, which is once again higher than the LMS that is stated in Table 4 as follows.

Table 4.

	Learn Wise	WebCT Vista	ECollege AU+	Proposed Model
Accessing Course notes	20	30%	20%	74%
Accessing assignment requirement	50%	20%	10%	67%
General navigation around the site	43%	34%	30%	79%

6.1 Comparison with baseline methods

The comparison of evaluation metrics is carried out—the statistical analysis of performance evaluation metrics such as the F-measure, precision, and recall [14]. To establish the precision of the suggested recommendation system, Figure 11 explains the collective comparison of the proposed recommendation system with state-of-the-art recommendation systems.

The dataset abbreviated as DS1 [46] has deep factorization machine technology, and content-based datasets acquired from social media websites were utilized. The precision of evaluation matrices is 0.53, the recall is 0.58, the accuracy is 0.70, and the F-score is 0.78 for DS1.

Wang is shortened to [DS2] after experimenting with a publicly available data set from Frappe, a context-aware knowledge discovery application [42]. In this study, collaborative neural filtering is employed. 0.56 recall, 0.58 precision, 0.52 f-score, and 0.78 accuracy.

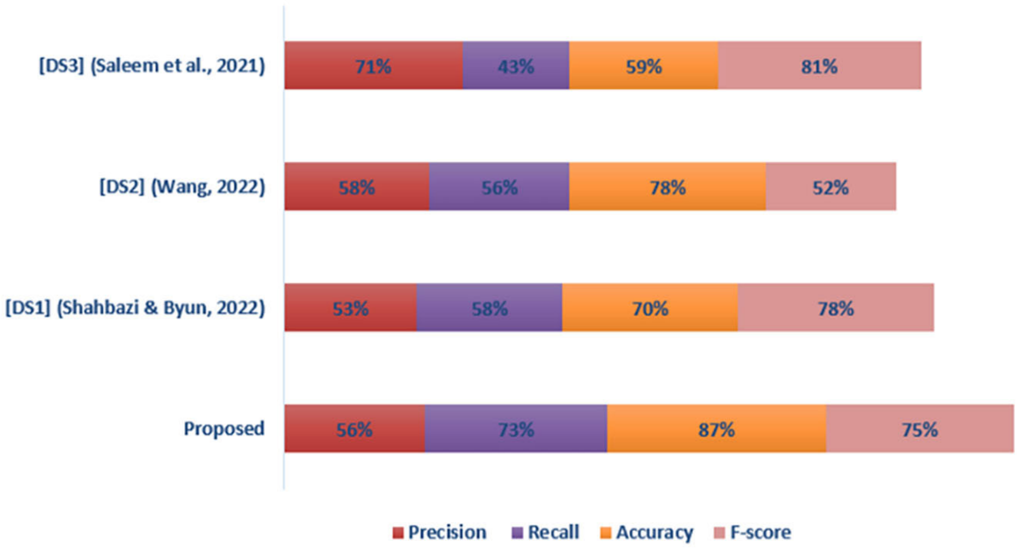


Fig. 11. Comparison of the proposed model with DS1, DS2, and DS3

Saleem, abbreviated as [46], acquired a data set from Kalboard 360 LMS utilizing a learner activity tracker tool and an ensemble approach in which the algorithm employed a decision tree, Nave Bayes, KNN, and gradient boost tree. Calculated precision was 0.71, Recall was 0.43, accuracy was 0.59, and the F-score was 0.81.

To have a better insight into the performance measures of the proposed recommendation system, individual evaluation with state-of-the-art recommendation systems is presented in Figure 13.

The discrepancies seen in precision, recall, and F-Score among the datasets can be a reason for many underlying variables. The decreased precision and recall of DS1 may suggest difficulties in effectively predicting relevant recommendations or contextual relationships within the dataset. On the other hand, the proposed approach surpasses DS2's recall, it suggests that the proposed system is better at gathering important information or successfully connecting contextual data for the goal of making recommendations.

The assessment of the proposed rising star ranking algorithm and contextual VISUWORD-based technique on dataset DS4 provides clear insights when compared to the current datasets (DS1, DS2, and DS3). Figure 11 demonstrates that DS1 displays significantly worse precision and recall metrics. On the other hand, the proposed approach demonstrates higher precision when compared to DS1. Nevertheless, the DS4 model demonstrates reduced F-score and accuracy when compared to the dataset under consideration. Significantly, the proposed system's recall measure exceeds that of DS2. In addition, when compared to DS3, the suggested approach exhibits improved accuracy and recall metrics, hence surpassing DS3. These data indicate that the proposed approach is more efficient and productive.

The proposed approach demonstrates superiority over DS3 through increased accuracy and recall, indicating its enhanced capacity to discover pertinent patterns or connections in the data, leading to more precise and valuable recommendations.

6.2 Statistical evaluation

Moreover, statistical measures are also applied to control and experiment groups for assessing the significance of our proposed model. Along with the observation of differences, this evaluation also strengthens the evidence of the proposed model's effectiveness. This is also obvious from Table 5, where a p-value of 0.02 is obtained. When comparing the calculated p-value with a predetermined significance level (often $\alpha = 0.05$) there is a significant difference between the means. The mean and SD of the control and experiment groups are presented in Figure 12. As evident from the figure, the experiment group performed better than our proposed model treated it.

Table 5. T-test results for post-test of two groups

Group	N	Mean	SD	p-Value
A	30	3.9	1.24	0.02
B	45	7.29	1.54	

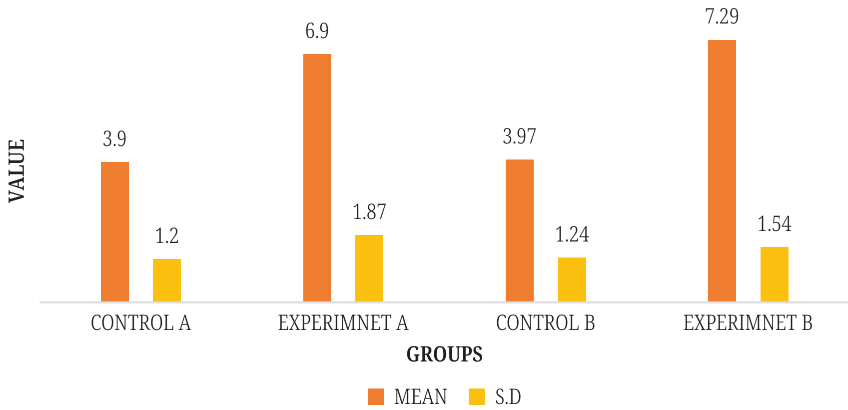
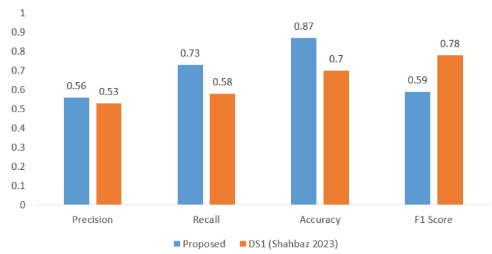
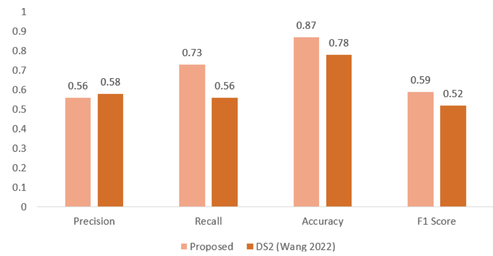


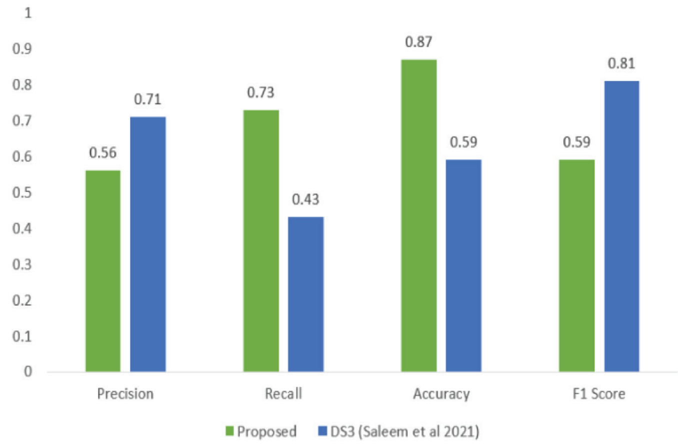
Fig. 12. Mean and SD of control and experiment groups



a) Compasrion of proposed model with DS1



b) Compasrion of proposed model with DS2



c) Compasrion of proposed model with DS3

Fig. 13. Evaluation of proposed model with state-of-the-art recommendation

In this part, the consequences of using the recommended model to evaluate the performance of learners in an e-learning environment are examined. The proposed model was found to be superior to other possible representations after a comparison with other methods that are already in use. In specific terms, it results in conclusions that are around 9% more accurate. The key reason for this achievement is the use of FCA and the rising star algorithm. In the context of the student performance problem, it is necessary to investigate performance metrics that illustrate how well the proposed model categorizes and ranks the instructional content making use of FCA and rising start. FCA can show concept hierarchies for multi-level recommendation systems. This allows recommendations that incorporate broad categories and personal preferences, making it beneficial for platforms with different content kinds and topics in LMS. FCA simplifies exploratory data analysis to find content and user preference trends and correlations. FCA works well with sparse data, which is prevalent in content recommendation contexts when users interact with limited learning resources.

The Rising Star, despite its limited recognition, holds potential value in the realm of content recommendation by assigning priority to recently popular or trending content. The platform provides users with novelty, randomness, and fresh recommendations, hence augmenting user engagement and encouraging the emergence of diversity. As a consequence of these amendments, the performance metrics and statistical indicators demonstrate that the proposed model possesses a higher recall and importance than its competitors. As a consequence of this, the strategy that was provided can be utilized to apply to real-world tools to locate potential contextual instructional content within an online learning environment. Moreover, our study highlights how these technologies can change and grow with the demands of education in the future, creating a more dynamic and responsive learning environment.

7 CONCLUSION AND FUTURE WORK

In the area of e-learning, measuring student cognitive abilities, performance and learning experience has received a lot of attention. Measurement of learning outcomes, selection of learning resources, and learning practices depend on student performance, development, and ability. Our proposed methodology is to predict 'students' performance in a distance education course that would alert the learners about their performance and offer an opportunity to improve their growth in the future. The primary aim of this study is to determine whether or not the course-related resource retrieval is improving for the student. The proposed approach has two main features: data processing via visualization and feature reduction via FCA, which results in rated content for recommendation through the Rising Star algorithm. Our study findings underscore the pivotal role of engagement and prioritized content in shaping the success of online learners, affirming its profound impact on educational quality. Furthermore, the adoption of a rising star algorithm for ranking course contents and contextual linking such as VISUWORD holds significant promise. Our assessments reveal that the proposed framework's f-score measure surpasses traditional training approaches by a noteworthy margin of 75%, highlighting its potential for substantial enhancement in educational outcomes. The proposed approach is essential for improving student performance and engagement, in addition to supporting flexible learning environments. These technologies play a major role in enhancing personalized learning experiences in addition to improving the quality and relevance of learning resources.

As we move forward, more research and development in this area should improve educational outcomes by combining collaborative filtering techniques and sentiment analysis to better understand and cater to the requirements and preferences of students. In future work, student results can be enhanced based on sentiment analysis and making the ranked content matrix based on feedback and reviews. In this study, the ensemble technique is missing to gather students' ideas and motivational behavior calculating cognitive aspects to gain better results for future researchers.

8 CONFLICTS OF INTEREST

The authors declare no conflict of interest.

9 AUTHOR CONTRIBUTIONS

Anam Zaheer, Sidra Tahir, Asif Nawaz have worked on Conceptualization, Methodology, Validation, Ahthasham Sajid has worked on Formal analysis, Investigation, Writing Original Draft, Muhammad Mansoor Aalam has worked on Review and Editing, Visualization and Prof Mazliham Mohd Su'ud has Supervised and provide Funding acquisition.

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