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Agent-Based Recommendation in E-Learning Environment Using Knowledge Discovery and Machine Learning Approaches

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Abstract: E-learning is a popular area in terms of learning from social media websites in various terms and contents for every group of people in this world with different knowledge backgrounds and jobs. E-learning sites help users such as students, business workers, instructors, and those searching for different educational institutions. Excluding the benefits of this system, there are various challenges that the users face in online platforms. One of the important challenges is the true information and right content based on these resources, search results and quality. This research proposes virtual and intelligent agent-based recommendation, which requires users' profile information and preferences to recommend the proper content and search results based on their search history. We applied Natural Language Processing (NLP) techniques and semantic analysis approaches for the recommendation of course selection to e-learners and tutors. Moreover, machine learning performance analysis applied to improve the user rating results in the e-learning environment. The system automatically learns and analyzes the learner characteristics and processes the learning style through the clustering strategy. Compared with the recent state-of-the-art in this field, the proposed system and the simulation results show the minimizing number of metric errors compared to other works. The achievements of the presented approach are providing a comfortable platform to the user for course selection and recommendations. Similarly, we avoid recommending the same contents and courses. We analyze the user preferences and improving the recommendation system performance to provide highly related content based on the user profile situation. The prediction accuracy of the proposed system is 98% compared to hybrid filtering, self organization systems and ensemble modeling.

Keywords: e-learning; knowledge discovery; machine learning; recommendation system; intelligent optimization

MSC: 68T30

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1. Introduction

In recent decades, e-learning has been measured with conventional learning processing to attain the learners' objectives [1]. Enhancement of the web user comes up with learning offline or online for the students, which is an e-learning method that is very effective compared with other techniques. Personalized e-learning allows learners to access any information at any time. The main interest between learners is the famous attribute of developing meaningful environments for users [2,3]. Specifically, the resources of learning are categorized into three groups: Collaborative Filtering (CF), Hybrid Filtering (HF) and Content-based Filtering (CB). In [4], a systematic overview of ontology-based e-learning recommendation is presented. This system examines and evaluates the technical aspects of an ontology learning system for recommendation. The CF recommendation evaluates the similarity of the content based on the learner's rating and prediction. This process suffers from the problem of sparsity that appears between items and users due to insufficient rating records. The main reason for there being no ratings from users is the lack of scoring time limitations of learning matching the high records of data sparsity, so applying the CF technique becomes tough [5]. The CB recommendation method gives content suggestions related to the learners' requests and preferences. The usage of social media in terms of education gives the opportunity of providing a user-friendly interface for recommending the highest interaction in terms of cooperation between users and contacts [6–8]. In [9], the effectiveness of multi-sensor data fusion for chatter detection was presented. The proposed approach measures the chatter occurrence using the microphone and accelerometer sensors. The results provide an effective chatter detection output based on the conditions of industry with a high accuracy compared to the traditional systems. In [10], a fuzzy entropy and feature selection model is presented for chatter vibration diagnosis. The system compares various machine learning algorithms with different feature selections. The presented system identifies chatter vibration with a low computational burden and higher accuracy than intelligent diagnosis techniques. In [11], the presented recommendation system designs the course types using content-aware filtering and innovative machine learning approaches based on the Learning Objects (LOs). This provides easy access and semantic searches regarding LOs. Regarding the significance of the e-learning system, most researchers study the educational recommendation system based on technologies related to education [12–14]. Zeshan et al. [15] proposed the Stochastic Gradient Descent (SGD) technique for a fuzzy-based recommender system. The SGD approach improves the efficiency of the recommender system by dealing with fuzzy behavior. This technique improves the accuracy based on the strength of the sliding window and utilizes the fuzziness between ratings. The main contributions of this paper are summarized below:

- Applying the NLP techniques for text mining and enhancing the trainer mentoring;
- Using agent-based recommendation to solve the limited user ranking problems and improve the performance of the e-learning environment;
- Updating the generated recommendation for each cluster to improve the quality of recommendations based on the extracted information from user profiles and search histories;
- Identifying the learning style based on the learner's characteristics and knowledge discovery on the collected information through users' activity.

The recommendation system framework is supposed to follow the user's expectations regarding the proposed approach. This process needs text mining techniques and semantic analysis based on user preferences. According to the explanations, the advantage of agent-based recommendation is to follow user requests without any inconvenience or interruptions. First, there is a need to create a list of suggestions based on the extracted input data and, second, to use user feedback to generate suitable recommendation results. Moreover, the comparison of the other state-of-art methods demonstrates the preferences of content-based and interactive recommendations from different e-learners and is more successful. The other benefit of this system is empirical proof and a road map of the educational system and future research.

The rest of the sections are divided as follows: Section 2 describes the recent works and techniques in an e-learning environment. Section 3 provides a detailed explanation of the proposed recommendation system for e-learners. Section 4 shows the development environment, performance evaluation, and experimental results of the proposed system, and, finally, the conclusion section.

2. Materials

This section discusses the related literature of the Recommendation System (RS) types, existing e-learning approaches, and the successful systems. Some of the e-learning systems are measured based on the specific feature of a learner, characteristics, and user information [16–19]. In [20], the proposed system is based on the user-based model generation to create the conductive educational process for the subsequent trades and professions. There are various techniques for building the user models based on their behavior and the complex nature of humans, such as applying a Bayesian network or a fuzzy-logic-based network [21–23].

2.1. Strategies of Recommendation

Regarding the real-time needs of learners, it is required to confirm the adaptive navigation and presentation. In the current research in recommendation systems, the main focus is on users' preferences and behaviors or the testing ability to regulate the strategy of recommendation [24–26]. For example, Jadidinejad et al. [27] set the point of research on user propensity for diverse item selection to evaluate based on the contents and attributes of the item. Ahmed et al. [28] applied an adaptive learning system based on automatically creating a concept map using data-mining techniques. Troussas et al. [29] presented a social-network-based education system to create an enjoyable and useful system, and they conclude it regarding the further investments and testing in digital technology. Olivares et al. [30] presented the social network analysis embodiment to overcome the needs of special education needs of learners. The knowledge of aggregation in the ontology domain related to sources of learning and learners improves the accuracy and quality of recommendation, and it reduces the conventional recommendation technique's associated drawbacks [31,32]. The mobile learning tool presented in [33] is based on the integration of real-world and digital-world contextual information to help learners for creating barriers regarding their excitement of the confidential material. Training the real-world environment in a Virtual Situation (VS) lets the trainees use the VS to manage the job in a proper way [34,35]. There are various studies in semantic-based recommendation approaches in terms of ontology [36] and e-learning recommendation in the area of artificial intelligence using self-organized maps to develop the learning path of learners [37,38]. One of the important online learning developments is Massive Open Online Courses (MOOCs), which gives a chance to the students to attend the learning process based on their condition and terms. This is a new learning way that is distributed, open, and lifelong. The lifelong concept gives a self-directed and responsible feeling to the student to choose their learning path. In [39], a review approach on Massive Open Online Courses (MOOCs) recommender system from 2012 to 2019 was presented. The main focus of this process is on academic databases such as Springer, IEEE, ERIC, etc. The Massive Open Online Courses (MOOCs) have been one of the recommender system solutions for many years. This approach enables the learners to fulfill their needs in distributed, participatory, and open ways.

2.2. Agent-Based Recommendation System

A huge number of materials and information are provided for the learners' tasks because the many educational sources contain various subjects. E-learning ameliorates the knowledge of learners and their abilities [40,41]. The concept of agent-based e-learning systems is carried out over an extensive area. In [42], web-based learning and the learner history and activity was proposed. The final result of agent-based recommendation is to set rules and check the connection between various items at the same time. In [43], the authors proposed the usage of the learning management system by proposing an agent-based voice-enabled assistant. This agent works based on the user's task and speeds-up the process of learning.

2.3. Knowledge-Dependent and Evaluation of Recommendation

RS tries to give the best result based on the user search request and preferences. This information contains the relationship between the achievable contents based on the user profile information and structure, which is the biggest information source to collect user knowledge. This process collects the information of the learning objects for utilization regarding the recommendation activities [3,44]. It is difficult to obtain the necessary ratings in terms of different properties and the huge rate of content mixtures. Gathering data for the specific learner is not possible due to the user's specific preferences. There are three main recommendation evaluations, namely, user's studies records, offline experiments, and online experiments [45]. The offline experiments use the available protocols and datasets related to user activities and recommendation accuracy. The restricted users and their feedback depend on the recommendation, and the online trials show the RS's real-time usage [46]. Table 1 shows the comparison between recommendation systems based on their advantages and limitations. In [47], the authors proposed an e-learning recommendation approach regarding the students' data in Madrid. In this process, the knowledge discovery approach is used to extract the teachers' selected information to generate the students' interaction in an e-learning environment. The presented approach used the real students' academic data.

Table 1. Recommendation techniques' comparison.

Applied Technique	Overview	Advantages	Limitations	Applications
Collaborative Filtering [48]	Highlighted different ways through which to enhance the information retrieval and suggested the proper recommendation regarding the improvement in performance and level of satisfaction.	The domain knowledge is not required. Information retrieval improves the effectiveness of the system.	The recommendation system effectiveness is not seen until compared with other domains	Novel Dynamic Evolution Mechanism.
Hybrid Filtering [49]	Type of book recommendation that comprises content-based and collaborative-based filtering prediction	Using spark big data to enhance the utilization rate of personalized book recommendations.	It has a time complexity issue.	Self-Organizing Map Neural Network Technique
Context-aware [50]	Gathering the data related to feedback and contexts from the learner module or sensors.	Recommendation regulated based on context.	Contextual information integration	-
Ontology-Dependent [51]	The recommendation focus on the learning and hybrid approach without ontology. The ontology uses different aspects of the context.	Overcoming the traditional recommendation limitations. Gives better performance in terms of hybrid recommendation.	Domain knowledge required. Correct recommendation identification. Evaluating the performance is difficult.	ASTM Standard Method
Cross Domain [52]	Comparing the potential item with the rated item in terms of specifying matching options.	Domain information not required.	Data sparsity, Scalability	PrefixSpan to generate sequential patterns. TopSeq rule mining to find frequent sequential rule.
Demographic [53]	Modifying and improving the new ways for financial planning recommendation.	The history rating of the special learner is not required.	Personal attributes must be retrieved from the learner.	LDA Approach

2.4. Comparative Analysis of E-Learning Recommendation

There are various platforms related to the e-learning environment to improve the quality of online studying. In this section, we compare some of the recent approaches in this area with the proposed agent-based e-learning environment mentioned in Figure 1.

In [54], the authors proposed the self-organization of learning sources in terms of e-learning recommendation. In this system, the simulation of learning objects is processed by considering the intelligent entities and using the theory of self-organization. Next, the module of environmental perception is designed to capture the learners' preferences, and finally, the recommendation is generated. The accuracy of this system defined as 76.3%.

In another approach in [55], the hybrid filtering approach for e-learning recommendation combined with self-organization theory was proposed. In this process, the Learner Influence Model is used for accurate information by evaluating the learner exerts related to others. The presented approach accuracy is defined as 84%. In [56], an intelligent decision support system to predict the performance of e-learners was proposed. This approach was designed based on five traditional machine learning algorithms and four ensemble techniques. Compared to other ensemble models, this approach has the highest accuracy of 81%. Using the prediction models improves the students' performance and helps tutors in their decision making. The above-mentioned systems show how the recommendation system appears in various systems. It is clear that the proposed recommendation system has a higher effect in the proposed recommendation process.

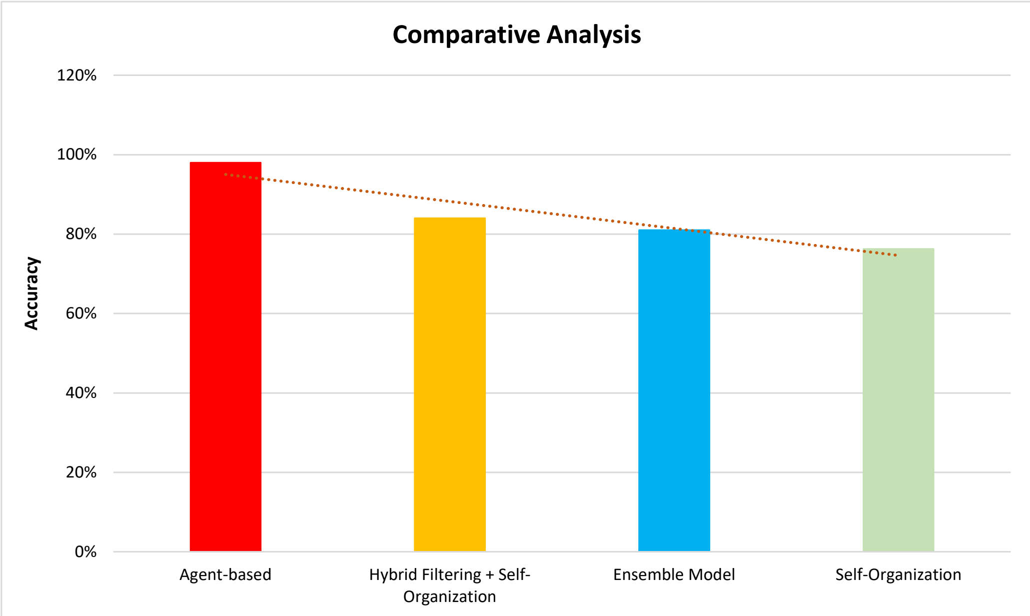

Figure 1. Comparative analysis of the recent approaches in e-learning environment.

3. Methods

In this section, the proposed system is based on knowledge discovery in an e-learning environment and its recommendations. The system follows the agent-based recommendation to address the e-learning environment problems. This architecture aims to recommend the proper document to users based on their search results and preferences. This process guides the student for course selection and improves the qualification and skills according to their concerns. Figure 2 shows the overview of the e-learner recommendation system. This architecture has three important phases: information collection, pre-processing, and recommendation. The collected information is from the users' and learners' profiles. The process of data pre-processing is defined into three terms: text mining, extracting terms, and mapping terms and opinions.

After pre-processing section, the data are ready to start the recommendation process. The first step of recommendation is user filtering. Next is the user rating, and last is the preparing the recommendation list. Table 2 presents the summary of the used notations during these steps.

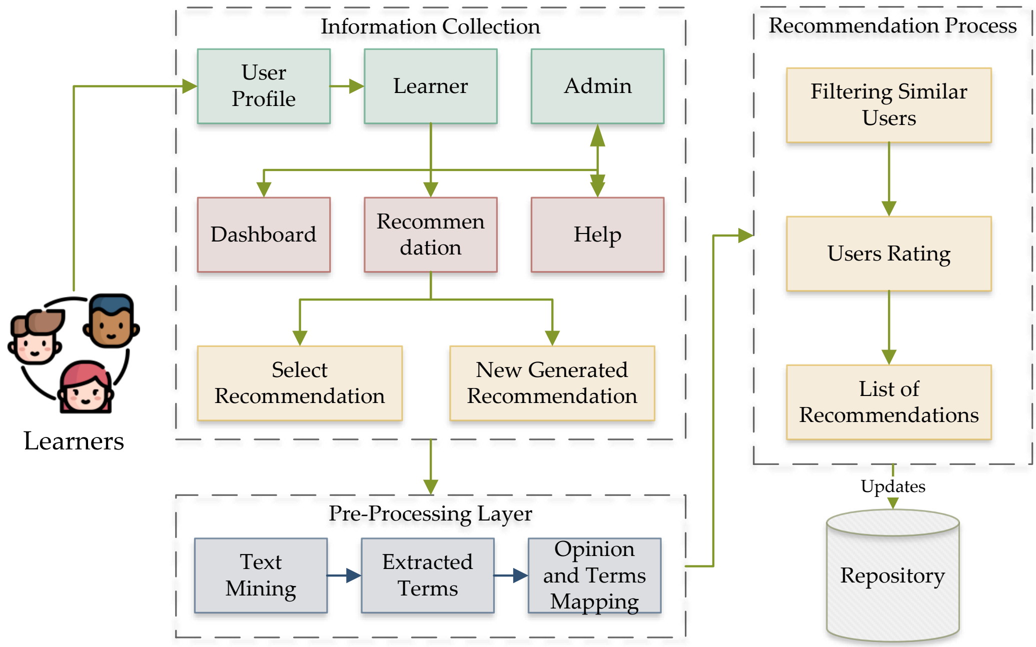

Figure 2. Overview of the e-learning knowledge discovery and recommendation architecture.

Table 2. Nomenclature.

Notations	Inference	Description
K_{pi}	Knowledge Point	$K_{pi} \in [1, n]$
I_{pi}	Level of importance	$I_{pi} \in [1, 5]$
D_{pi}	Level of difficulty	$D_{pi} \in [1, 5]$
S_{pi}	Size	S_{pi} is a digit
A_{pi}	Attributes of media	$A_{pi} \in [1, 6]$
C_{pi}	Attributes of content	$C_{pi} \in [1, 5]$
L_{pi}	Learning time suggestion	L_{pi} is a digit
M_{pi}	Constraint matrix	M_{pi} is $M_{pij}, i, j \in [1, n]$ matrix
QK_{pi}	Current state	$QK_{pi} \in [1–4]$
QI_{pi}	Ranking of similarity	$QI_{pi} \in [1, n]$
QA_{pi}	Marked labels	$QA_{pi} \in [1–4]$
QL_{pi}	Visited time	$QL_{pi} = vt_{pi} \mid J_{pi}$
QC_{pi}	Visited frequency	QC_{pi} is a natural digit
W_{pi}	Weight	$W_{pi} \in [1, n]$

3.1. Information Collection

After profile creation, the management system collects the data and demonstrates the process. Then, the users who have access to the management system can also access various course options for learning. Following the process, the data collected regarding their interest, qualification, expertise, etc., are saved into the database for future recommendations. The data are extracted from an agent process with semantic analysis and text mining techniques for the suitable and correct recommendation. In this process, the data collection is a user request for the data mining recommendations for courses and tutors after checking the information of users' experience in jobs, requirements, and skills. The processed skills from the user is used by the agent, and this can recommend a suitable tutor for the user based on the search results to enhance the user experience. Figure 3 shows the details of the e-learner profile interface in the proposed agent-based recommendation system.

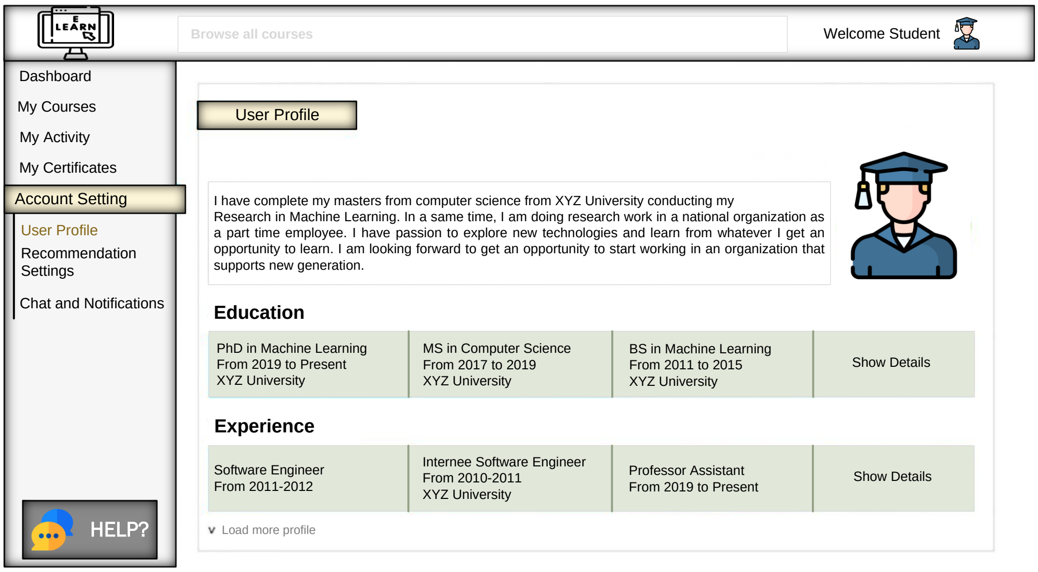

Figure 3. E-learner profile interface.

3.2. Domain Knowledge

The main concepts of this system are rules and problems during the learning process. The domain knowledge contains Python designs in three levels: basic, intermediate, and advanced. Figure 4 shows the logic of the defined system.

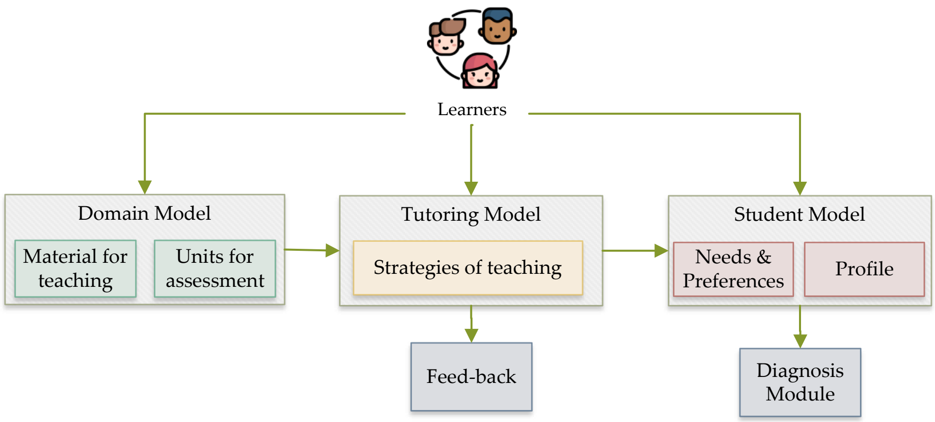

Figure 4. User interface based on social network logic overview.

The student model is one of the initial components of this system. It focus on the characteristics, strengths, and weaknesses and, based on this, further processes the learning approach. During this process, the student's profile and personal information are considered to create the learning experience and detect system errors that users can make. The tutoring model is the other model of this architecture, which shows the teaching strategies and confirms the requests from students based on their selected domain and similarly decides tutoring processing. Regarding the input of the student model, the system gives the feedback of student requests during learning and study situations to reach a good stage of knowledge acquisition.

3.3. Recommendation Framework

The recommendation problem in the e-learning system is complex in terms of various constraints, e.g., goals of learning, preferences of learning, and limitation of time. The goal of the recommendation system is to overcome these issues together. GridSearch is applied in the proposed system for adjusting the recommendation parameters. Figure 5 shows an overview of the agent-based recommendation framework. This framework has three main modules: a learning module, a recommendation module, and an interactive module. The learner module is responsible for quantitatively evaluating learners' similarity, the credibility of knowledge, and learners' aggregation. Profile and personality similarity are evaluated based on the similarity between learners. The credibility of knowledge evaluates learners' behaviors and scores. The aggregation of learners analyzes the learners transaction process. In the recommendation module, the agent-based recommendation is supposed to simulate the learners' environment and theory organization. The interactive module evaluates the learners' activities, e.g., study records and tagging behavior.

Figure 6 presents the details of e-learner profile based on the user rating and the agent-based recommendation system.

The presented agent-based recommendation contains the domain, learner, application, adaption, and session subsystem. The details of every subsystem are summarized in Table 3.

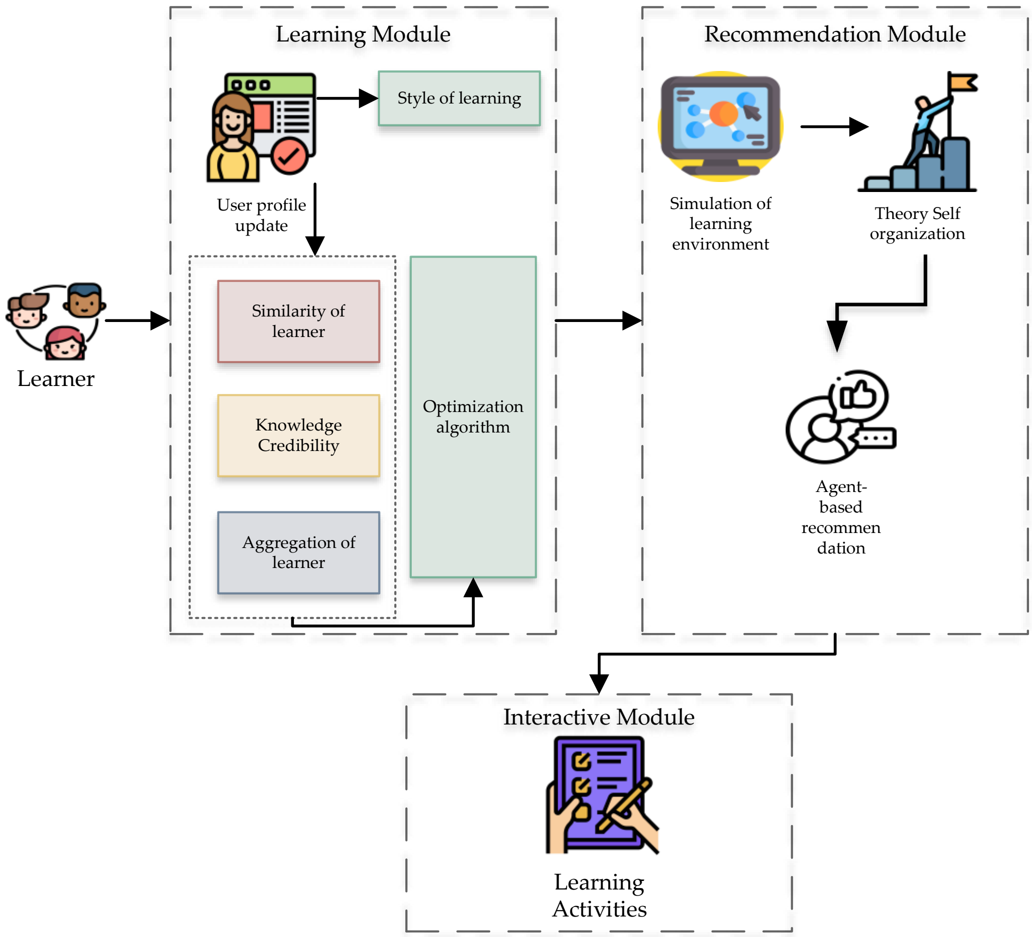

Figure 5. Overview of the Agent-based recommendation.

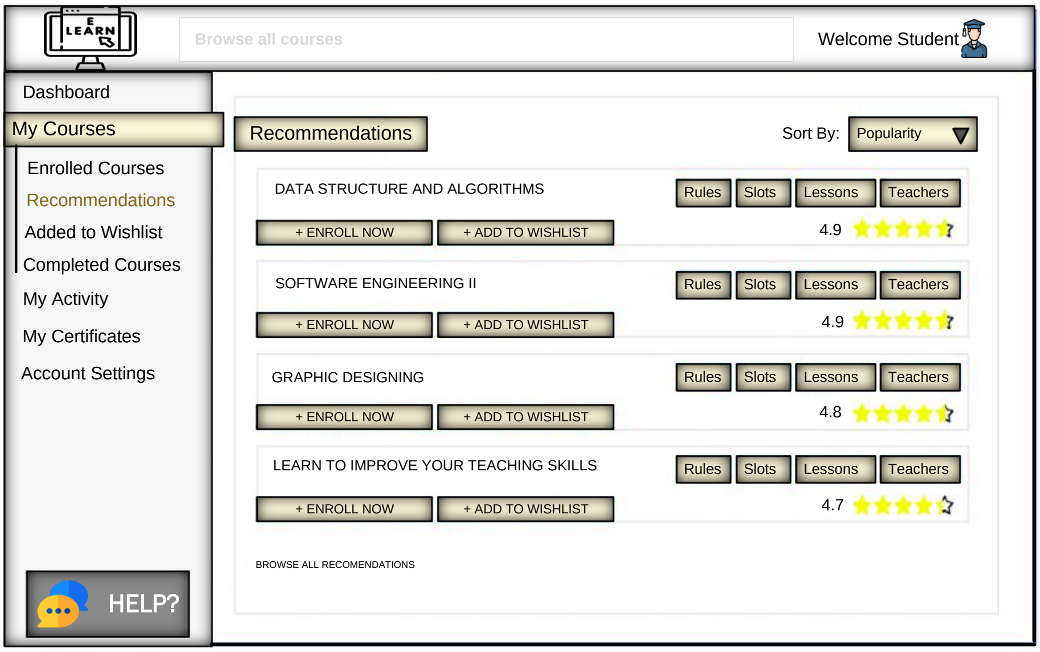

Figure 6. E-learner profile recommendation interface.

Table 3. Recommender system subsystems.

Subsystems	**Process**
Domain	Saving the various components and resources of learning
Learner	Extracting the features and information of the learner
Application	Identifying the learner's requirements by adding the operational rules
Adaption	Learner's agent identification based on intelligent recommendation
Session	Subsystems controlling the main system

Enhancing Trainer Mentoring Using Text Mining

Through the recommendation process, the agent finds the suitable choice for the e-learner regarding the e-learner's preferences. Different recommendation processes are used in various works, such as content-based filtering based on user ratings and user profile information to pick the suitable recommendation. The other recommendation method is collaborative filtering and the hybrid recommendation is combined of the other mentioned approaches and yields better results. The hybrid approach gives the information to the e-learner recommendation architecture and analyses all the measures of the user's information in detail. Algorithm 1 presents the step-by-step process of the agent-based recommendation based on the users who completed the courses and users who are currently taking the courses.

Algorithm 1 Learners' Similar Course Set.

Input: User interested courses set
User repository existing courses
Output: Recommended courses based on user interest
Train Step:
for trace and identify the recommended courses **do**
  if $Course.Recommendation_i \in$ Course Selection **then**
    Update the parameters of the model
  end if
end for
Test Step:
for $\forall$ $Course.Selection_i \in$ Course Selection **do**
  sampling output based on training model
  return Set of recommended courses
end for

4. Predictive Analysis of Agent-Based Recommendation

In this section, the data processing details presented. Figure 7 shows the detail of the agent-based recommendation predictive analysis process. There are three main sections in this approach. The first one is data-attributed collection, which contains the user's information, tweets, photos, date, time, retweets, and comments shared on social media. The second section contains the data-processing approach, which, in the first stage, pre-processes the collected dataset, then performs feature extraction, data transformation, and feature selection and splits the dataset into train and test sets. We applied 80% for the training set and 20% for the test set in this process. The final section is the recommendation which recommends the courses based on the collected data from users' shared information. To avoid the over-fitting problem, the cross validation, feature selection, and early stopping point are considered in the process.

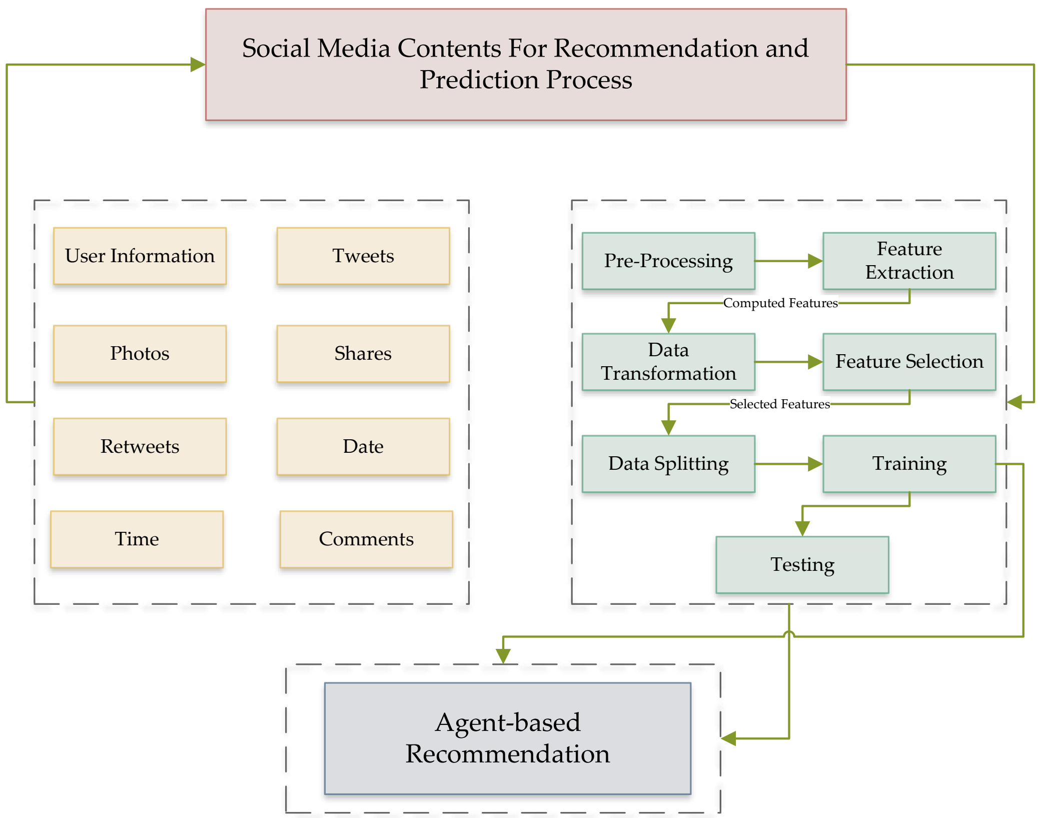

Figure 7. Predictive analysis architectural diagram.

Equation (1) represents the number of tuples regarding the e-learner's current knowledge level. Each of the listed attributes are evaluating the information-related media preferences, the content preferences which refer to the e-learner, the purpose of learning and objective of education, and the learner's attitude regarding knowledge acquisition:

$$Set.of.Attributes = K_{pi}, I_{pi}, D_{pi}, S_{pi}, A_{pi}, C_{pi}, L_{pi}, M_{pi}, QK_{pi}, QI_{pi}, QL_{pi}, QC_{pi} \quad (1)$$

Equation (2) evaluates the weight W_{pi} of the process belonging to the knowledge point, similar contents, and similar media:

$$W_{pi}^{d} = EC_{pi} | \sum_{i=1}^{n} EC_{pi} \quad (2)$$

Equation (3) presents the importance of the knowledge process by using the W_{pi}^{s} and W_{pi}^{d}. This process updates the importance of the whole system:

$$K_{pi} = k_{pi} * (1 + (W_{pi}^{s} + 2 * W_{pi}^{d})) \quad (3)$$

Equation (4) presents the difficulty of knowledge extraction process. This system updates the difficulty rate of the presented system:

$$D_{pi} = D_{pi} * (1 + (2 * W_{pi}^{s} + W_{pi}^{d})/3) \quad (4)$$

5. Results

In this section, the details of the development environment are briefly explained. Table 4 shows the details of the proposed system environment.

Table 4. Specifications and systems components.

Components	Description
Operating System	Windows 10 64 bit
CPU	Intel(R) Core(TM) i7-8700 CPU @3.20 GHz
Memory	32 GB
Programming Language	WinPython 3.6.2, IDE Jupyter Notebook
Browser	Google Chrome
Recommendation Module	Agent-based Recommendation
Library and Framework	Web Service
OS Manufacturer	Microsoft Corporation
OS Edition	Professional

5.1. Dataset

The presented recommendation system was analyzed on the content-based dataset collected from social media websites such as Twitter, Facebook, etc. The system extracts the hidden parts of dataset information for better performance from the process. This process contains the pre-processing, normalizing dataset, and extracting the useful information which is necessary to the processed topic. Data pre-processing prepares the dataset to become suitable for the system input. In this step, it is required to remove unnecessary contents and phrases to obtain the better performance results. Table 5 shows the extracted features from the collected e-learners' information.

Table 5. Extracted features.

Features	Description
User Information	The details of the user profile
Tweets	Contents shared by the user
Photos	Photos shared by the user
Shares	Links or contents shared on social media
Retweets	Re-posting the published information
Date	Date of published information
Time	Time of published information
Comments	Ideas about the shared contents

5.2. Performance Evaluation of the Proposed Agent-Based Recommendation

The performance evaluation presents the model output improvements and results of the system processing. The analysis of essential courses are based on the user profile and experience. The user feedback shows the e-learning system opinion mapping. Table 6 shows the details of the similar courses records between three learners and four courses. The defined "Yes" means courses are similar, and "No" means not similar.

Table 6. Courses similarity.

Learner (L)	Course 1	Course 2	Course 3	Course 4
L1	Yes	No	No	No
L2	Yes	Yes	Yes	No
L3	Yes	Yes	No	No

Table 7 gives the details of the positive, negative, and neutral feedback of users using the data-mining methods mentioned, namely, semantic analysis, topic modeling, and clustering. The result shows the e-learners' preferences for various topics.

Table 7. Results of opinion mapping.

	Method	Positive	Negative	Neutral
Data Mining	Sentiment Analysis	10	4	5
	Topic Modeling	11	3	6
	Clustering	8	3	4

The identified attributes of the recommender system were collected from students' online records from social media websites. To avoid over-fitting, the python kernal 3.1 was used to predict the system input to the particular classes. The classifier parameters are tuned by applying the hyperparameter tuning technique of GridSearch. GridSearch allows for an easier understanding of the differences between the training and testing accuracies with automatic tuning. GridSearch is one of python's sklearn library functions that is used for hyperparameter tuning. Figure 8 shows the details of the accuracy curve of the presented semantic analysis.

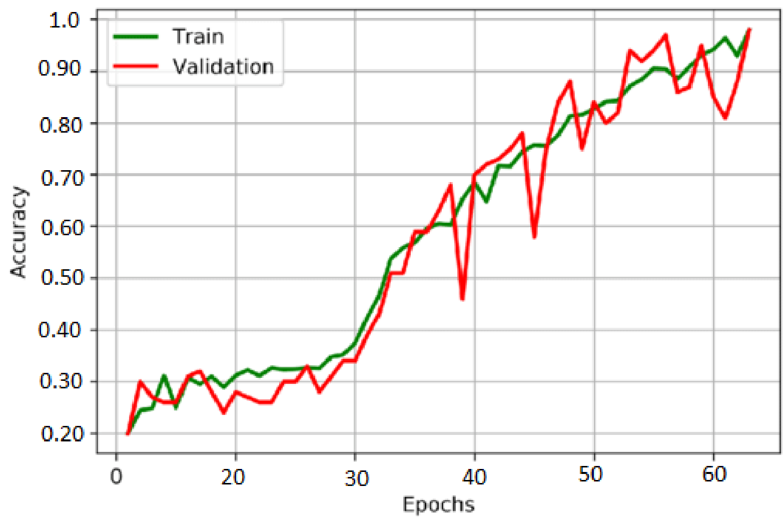

Figure 8. Accuracy curve of the presented ML semantic analysis.

5.3. Evaluation of Learning Experience

In terms of capturing the subjective experience of learners in the recommender system, Table 8 shows the satisfaction rate between users. In this process, we defined the satisfaction rate as a value between 1 and 5. A value of one means very unsatisfied, two means unsatisfied, three means only okay, four means satisfied, and finally, five means very satisfied. The SI in the Table defines the similarity between parameters. Prefix defines the access pattern rate. SI-Top gives information related to the highest recommendation based on the learner's target, and Tra defines the traditional teaching strategy in the classroom.

Table 8. Learners' experience evaluation.

Categories	Options	Tra	SI-Top	Prefix	SI-FL	SS-IFL	SSC-IFL	SI-IFL
Quality	Usefulness	4.4	4.8	4.4	4.6	4.8	5.0	4.5
Evaluation	Satisfaction	4.6	4.3	4.4	4.5	4.9	5.2	4.4
Personal	Difficulty	4.8	4.5	4.3	4.4	4.8	4.7	4.9
Realization	Media	4.4	4.9	4.0	4.7	4.5	4.8	4.7
Evaluation	Time	4.9	4.2	5.2	4.9	5.0	5.0	4.5
	Content	4.5	4.6	4.5	4.7	5.0	5.0	5.0
Experience	Attention Focus	4.6	4.8	4.5	4.7	4.9	4.2	4.9
Flow	Control	4.6	5.0	4.7	4.2	5.4	4.4	4.3
Evaluation	Curiosity	3.7	4.4	4.2	4.0	4.3	4.6	4.8
	Intrinsic Interest	4.4	4.8	4.9	4.4	4.9	4.9	5.0

The system database is summarized in Table 9 sorted based on the ID of learner, and the date and access path to courses.

Table 9. Sorting result of learning resources.

ID of Learner	Date	Access Path
1	1 December 2021	Course 1
2	2 December 2021	Course 2
3	3 December 2021	Course 3
4	4 December 2021	Course 1
5	5 December 2021	Course 1
6	6 December 2021	Course 2
7	7 December 2021	Course 2
8	8 December 2021	Course 3
9	9 December 2021	Course 1

5.4. Comparison of the Agent-Based Recommendation Performance Metrics

The performance of the agent-based recommendation system was evaluated based on various measurements. Due to providing suitable recommendations to users, the knowledge point, level of importance, difficulty level, size, time, media and content attributes, learning time, weight, and current state are considered as evaluation metrics. The main reason for selecting these metrics is to extract the proper knowledge based on user-provided information. The comparison is with the collaborative filtering approach using the Mean Absolute Error (MAE) shown in Figure 9. When the MAE is lower, the recommendation is more effective.

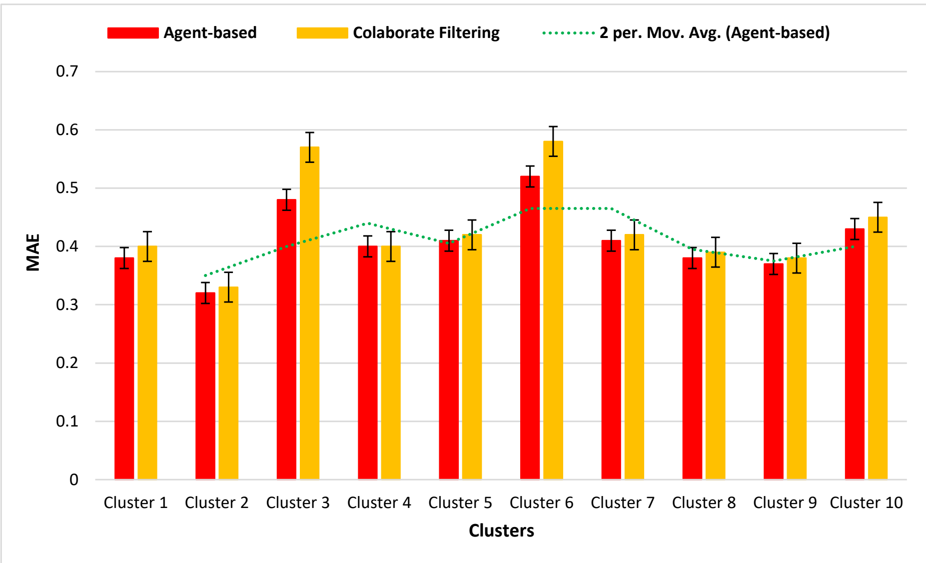

Figure 9. Comparison of performance metrics.

Figure 10 shows the simulation and non-recommender cluster mean time records. The times for each simulation cluster and the non-recommender cluster were measured separately. As shown in Figure 10, the time reduces in terms of the simulation cluster process. The Mean Time is the minimum taken time of each course.

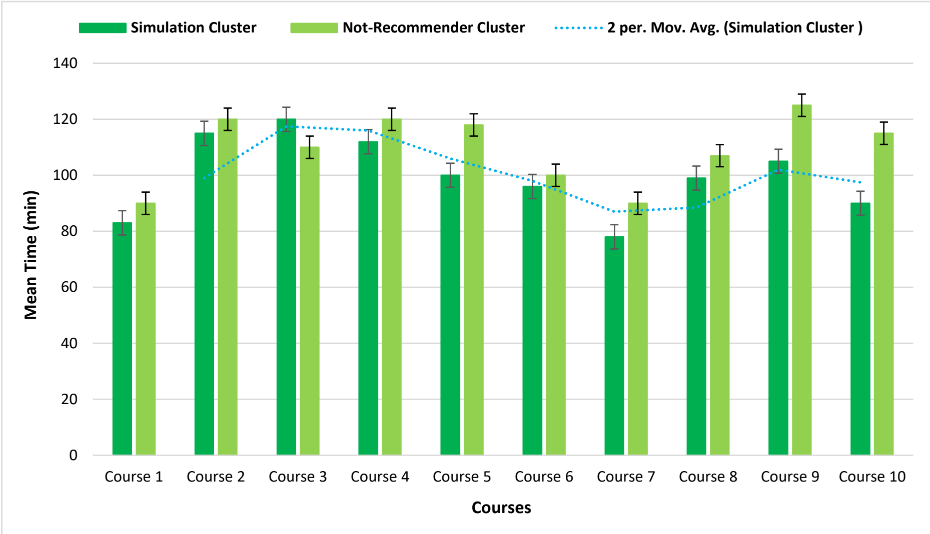

Figure 10. Evaluation of simulation clusters and non-recommender system mean computational time.

Figure 11 shows the awaited numbers of courses completed in the simulation and non-recommender clusters. The differences in checkpoints are uniformly considered as completed courses. As shown in Figure 11, the performance of the presented recommender system improved. As demonstrated from simulation clusters, learners completed more courses than the non-recommender cluster. The checkpoints are used to see if the course is completed or not.

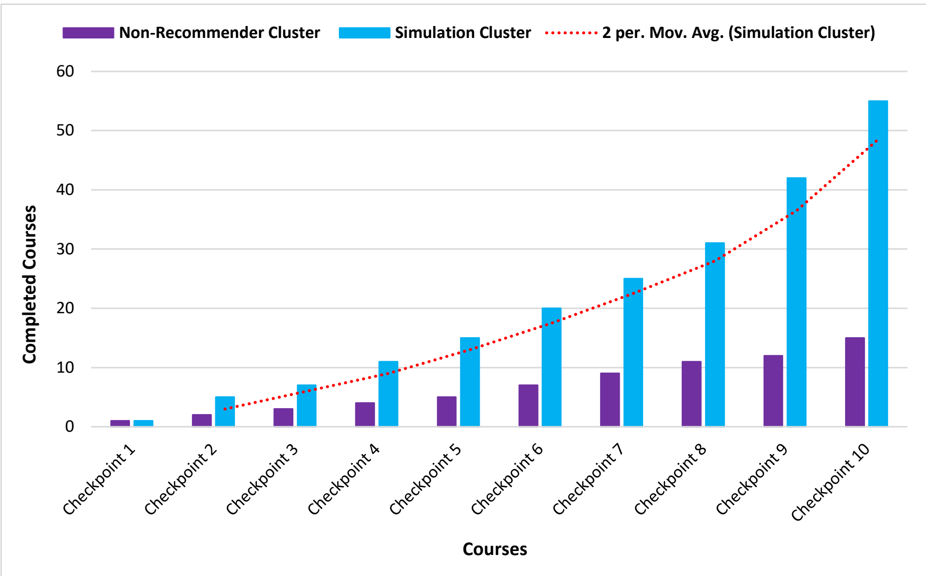

Figure 11. Completed lessons of learners based on simulation clusters and non-recommender expected time.

Figure 12 shows the average value of the diversity statistics for the learning period. It shows that the SI-IFL gives the highest diversity result in terms of difficulty and content. The degree of diversity shows the variety of contents which e-learners prefer to study. Further results presented in Appendix A.

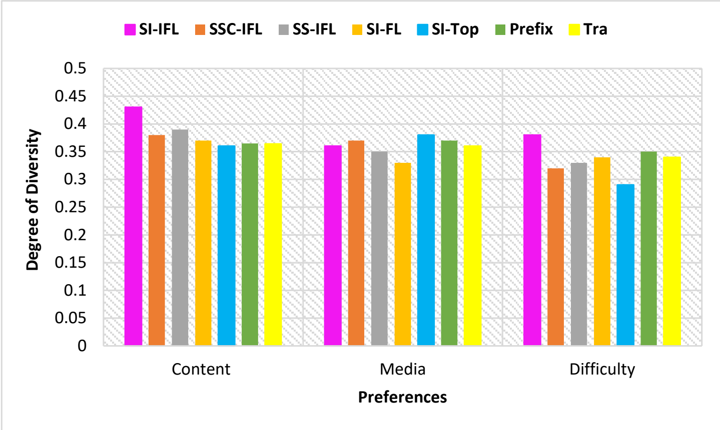

Figure 12. Evaluation of diversity of various attributes.

6. Discussion

This study presents the agent-based course recommendation for the e-learning environment and provides accurate results compared with the other traditional approaches. The selection is based on the users' preferences and interests, which is the main and important success for this e-learning system. This research presented the combination of NLP techniques with semantic analysis and data mining approaches to enhance the recommendation process to benefit the users' selections.

7. Conclusions

A recommendation system is one of the important aspects of a machine learning system. The importance of this system in e-learning environment increase day by day, and researchers try to solve the issues of this process. Agent-based recommendation is one of the suggestions for this environment which provides the multi-prospective suggestions considering the aspect-based analysis that supports the students and tutors in selecting the proper course based on their preferences and business demand. This process is not only a course assistant. It also gives real-time assistance during the course duration. While selecting an interesting course, the agent gives various perspectives without unnecessary recommendations to enhance and improve the learner's skills and online learning process. This process contains the knowledge development skills to find the proper course for students and teachers. A recommendation system is a strong approach which can makes the learning process of e-learners more convenient and easy to study the topics and courses that interest them. For future work, we will enhance this system by using other algorithms with further focus on e-learning systems. One of the aspects which we consider for future research is focusing on gaming in the leisure time and, based on the user profile and hobbies, recommend the proper game for making the learning process more enjoyable.

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Appendix A

This section provides the further details regarding the proposed system. The agent-based recommendation is estimated based on four factors, reliability, accuracy, speed, and simplicity, summarized in Figure A1. It can be seen that more than 80% of learners examine all the criteria for the evaluation of the recommendation system. The course simplicity records are taken from the user profile based on user rating and comments regarding the selected course.

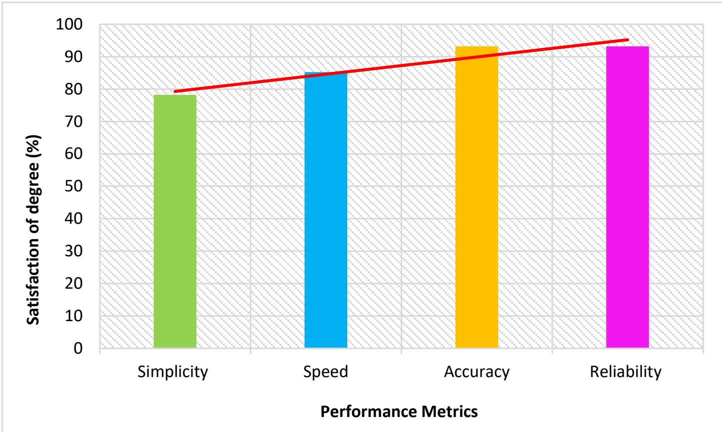

Figure A1. Agent-based recommendation evaluation results.

The learner's proportions are defined as difficulty later in the recommender system. Figure A2 shows the higher proportion groups as Tra and Prefix in both difficulty and later terms. It is noted that the traditional teaching method can not fully show the students' level of knowledge, and students can easily become bored from studying. Proportion means the relationship between the selected factors to compare them in terms of difficulty.

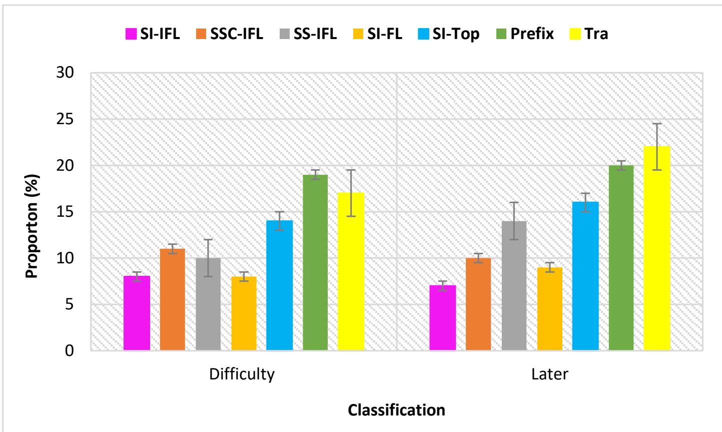

Figure A2. Marking proportions comparison of the proposed recommendation system.

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