Enabling Remote Learning System for Virtual Personalized Preferences during COVID-19 Pandemic

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Abstract

The education system around the world has been affected by the Corona Virus Diseases 2019 (COVID-19) pandemic, resulting in interruption of all educational institutions. Moreover, as a precautionary measure, the lockdown has been imposed that has severely affected the learning processes especially assessment activities including exams and viva. In such challenging situations, E-learning platforms could play a vital role to conduct seamless academic activities. Despite all the benefits of online learning systems, yet there are some difficulties and complications faced by users such as, selection of suitable learning material and courses according to the user's personalized preferences and resolution of the issues associated with the online virtual environment. Therefore, a mechanism is required that intelligently predicts the preferences regarding to request of diverse perspectives users for accurate and appropriate preference selection to improve the skills and knowledge of the learner in an interactive manner could be a remedy in this regard. In this work, an intelligent system is proposed which constructs semantic predictions with the help of virtual agent as per user requirements and preferences that help academicians in finding suitable preferences in real environment. The experimental and statistical results have demonstrated that proposed virtual personalized preferences system has improved the overall academic activities as compared to existing method. The proposed system not only enhances the learning abilities of the user but also facilitate them in course selection according to their interests and preferences.

Keywords: Distance education and online learning, COVID-19, Augmented and virtual reality, Recommendation System, Teaching/learning strategies, Architectures for educational technology system, Text Mining.

1. Introduction

Endeavors to shoot the spread of COVID-19 through non-pharmaceutical intercessions and preventive estimates, for example, social-removing and self-segregation have incited across the board conclusion of the scholarly world in more than 100 countries [1]. Previous episodes of irresistible sicknesses have provoked far reaching school closings around the globe, with fluctuating degrees of success [1, 2]. Calculated displaying has demonstrated that transmission of a flare-up might be deferred by shutting the scholarly community. In any case, adequacy relies upon the contacts youngsters keep up outside of study condition [1, 3, 4] that might be successful when sanctioned speedily and impact severely global education system. This tragic situation closed forcefully all educational institutions temporarily all over the world and decrease the moral of students and teachers about good quality of education for better knowledge and success in their careers. As many institutions i.e. schools, universities and colleges which provide on campus education closed and few of the institution's shifted to remote education due to this challenging situation overnight.

The online learning system shares knowledge globally using web applications and remote tools for conducting education services [5–8]. In eLearning environment, sharing of the knowledge require internet facility for both learner and teachers that are located dispersedly to get and provide education anytime and anywhere by using advance skills and technology [5, 9–11]. Provision of required skills, knowledge and advancement in curriculums and technology under traditional or on campus education specially in underdeveloped areas are difficult. Where there is less availability of internet with limited and less qualified [12, 13] resources. Therefore, main challenges are being faced by these institutions in COVID-19 crisis to accept change and adopt advance technology for education. These institutions have few technological options for conducting online classes and educational activities under limited budget and resources without compromising the education standards. Thus, institutions especially universities shifted their education system from on campus to digitalized according to dire requirements of current pandemic situation. Consequently, quality of education through eLearning at crucial stage due to overnight shifting from campus education to online education. The reasons are that students have to learn and arrange advance technology in shortest time to cope up with current scenario requirements without compromising their education quality and requirements [14, 15]. Similarly, most of teachers also have lack of knowledge and skills about advance technologies that are used in online education. Therefore, both students and teachers require a substantial amount of training and arrangements of resources required for the online education. Hence, the issues are not that how to provide quality education, it is how educational institution handle massive number of students in online education? Because, institutions will be assessed on their ability to adapt changes in term of technology and maintaining the quality of the educational contents. As it is difficult to shift all staff, teachers and students to online classes with their syllabus online overnight due to dispersed locations, and personalized preferences for learning and teaching [6, 11, 12]. The google and Microsoft products such as google classroom, Gmail, Duo, google forms, Microsoft team has helped the institution shift from on campus to online education. The major problems includes dealing with different online advance technologies for education, different errors during downloading, installation, internet speed, accessibility, video and audio. This makes the environment less engaging, confusing, and boring for students and their personal attention or individual interaction with the teachers become prominent issues during online education. Similarly, for teachers and admin staff the problems such as hassle, time management, burden and fatigue are also visible. The burden of teacher increases while demonstration during practical subject using advance technology. Both teachers and students need to learn about these modern technologies. Therefore, with the adaption and searching of new technologies and resources for online education, there is need of guiding and training for students and teachers to enhance their skills and knowledge about online learning methods [11, 12, 16]. For training and guidance students and teacher required personalized preferences about digital literacy [8, 9, 15, 17]. This will help them in selecting the right technology and skill set which are the prerequisite to use advance technology.

Keeping in view the problems identified above, there is need of a system which provides personalized option for online education to recommend both learner and teacher to lean and teach according to their preferences [13, 18, 19]. Whether relevant regular courses or degree and relevant to short courses for maintaining quality and standards of education by enhancing their skills and useful with current modern technology available for online education according to their benefits. Therefore, most of predictions based on collaborative based filtering (CBF) and content filtering (CF) to use previous user experiences and current user information respectively. To help leaners for identification of relevant material and experiences according to their viewpoints, feedbacks and experiences. Therefore, personalized preferences predictions based on former and current user information and rating [11, 12, 16, 20]. Hence, problem arises in personalized preferences prediction are semantic analysis, and term mismatch in preferences [12, 15, 21]. Another major issue is virtual assistance 24/7 for learners to guide them and resolve their issues.

In accordance with the current crisis and personalize issue mitigation we proposed virtual remote learning system for personalized preferences predictions using hybrid filtering (HF). HF is the combination of CBF and CF for correct semantic analysis and term mismatch issues resolution. For this we developed web-based prediction system for improving personalized preferences using virtual assistance. The proposed system designed to predict relevant preferences of multi user perspective based on sematic analysis to help user for accurate selection of contents and courses to enhance their skill and knowledge.

1.1 Research Contribution

Major contributions of the present study is to resolve personalized preferences during online education issues are as follow:

1. In this study, we identified that online education lacks the personalized preferences of learners and teachers virtually. Therefore, to handle virtual personalized preferences semantically, there is a need of a system for an accurate prediction of personalized preferences in multi perspectives according to their skills and experiences.
2. The proposed system predicts personalized preferences based on semantic analysis using text mining technique and hybrid filtering. The student and teacher preferences on demand are analyzed by the virtual agent semantically using text mining. Then predict list of personalized preferences by analyzing previous and current similar students or teacher's preferences consists of knowledge, experience and skill. The list of predictions classify according to rating of current and previous students or teachers' feedback.
3. Later, an empirical evaluation was performed for the verification of the proposed system. Real scenario was used to followed that justifies the validation of the proposed system. Our proposed system outperformed as compared to others without personalized prediction method.

4. The present study provides a pathway for the future practices and research work which provide overview and experiential proof for dealing with pandemic situations in education field using information technology benefits.

The rest of this paper is organized as follows. Work related to this area is reviewed in Section 2. In Section 3, we have given details about the proposed system. Empirical evaluation results and discussion in Section 4 about proposed system effectiveness investigation in current pandemic situation. At the end, concluded overall research work and recommend some future work in Section 5.

2. Related Work

A significant quantity of literature has been published on detecting benefits of online education that helps in getting skill and experience during online distance education. Also, there are many studies which describing need, role and recent trends in online education for improving recent challenges of online education.

Therefore, many researchers have argued that the need of preference recommendation in virtualized environment is considered as an important element in online education [12, 22]. To improve the tutoring and counseling services automatically with personalized preferences, online leaning with virtualized assistance gained more momentum in industry and research [11, 22]. Therefore, researchers have examined different challenges in online learning such as communication between tutors and students [11, 12]. Students source selection preferences, student tests/quizzes and examinations etc. are involved to retrieve the related preferences with online assistance using accurate mining and analysis procedures [13, 21, 22]. The existing techniques are mainly concerned with previous information of user by predicting some set of subjects using recommendation system, but they fail in case of current and new user due to lack of proper retrieval of information and information change relevancy for multi perspective user semantically. In contrast the present work has modified the issue of online learning performance by learners and teacher's accuracy to their experience, skills and requirements.

The author in [23] explored the employing online system using mobile learning platform to combine digital and real-world contexts. It can assist learners in flaws searching to trigger their enthusiasm with familiar contents. Similarly, a study by [14] identify the gap of E-learning improper and wrong combination of courses recommendations using data mining method. Evaluated by comparing proposed method with Model system, results depicted that its helpful for selecting and extracting course material for skills development. The recommendation of large number of user preferences combination by profiling the users experience and skills using data mining procedures i.e. classification, clustering and association rule mining to improve learner skills according to their interests [24]. In e-learning reuse of information to optimize recommendation [11] explore different platforms and identify the role of ecosystems for knowledge sharing in virtualized learning. Use of chronological information for recommendation helps in managing large information set and scalable learners [12]. While to increase the competence performance of online learner by recommending information based on previous similar learner performance level and also by using visual analytics for online assistance [6, 21].

Virtual environment (VE) based training simulates a real environment and allows trainees to step into VE to deal with task conduction [17, 22, 25]. Additionally, two-dimensional (2D) or fully immersed (3D) interfaces used in VE [22]. VE training could be used as a stand-alone training method and needs reuse of former similar users rating and current user previous preferences or interests semantic based intelligent recommendations using data mining to deal with multi user perspective [15, 17, 18]. the author in [13] presented OntoSIDES, which is core of ontology-based learning system in educational content. It traced the students' activities to improve their semantic relation. As to improve information prediction there is need to reduce irrelevancy and redundancy intelligently during information classification [18, 21, 26]. The problem of accurate selection of preferences, virtual assistance, multi perspectives, students/teacher's performance, extraction of relevant contents and maintaining education standard after COVID-19 crisis and situation. As COVID-19 situation impact education system mostly and change behavior of students, and teachers after shifting to online education. Hence, online education in current situation more appropriate solution and appropriate technology adoption and selection difficult to maintain higher satisfaction [1–4] and education quality [3, 27, 28].

Consequently, an in-depth review of the existing approaches has highlighted some limitations that lead us to propose system to overcome these limitations of the existing approaches during pandemic crisis. For example, no semantic information extraction [19, 21, 29] suffers from ambiguity and misinterpretation of viewpoints, multi perspective analysis ignorance problem identified [14, 30] which demotivate teachers and students to explore solutions and enhance knowledge. Ambiguity, incompleteness and redundancy in course descriptions contents, without virtual assistance [17, 22] increases the coordination with relevant personnel and performance issues. Therefore, there is a need of an easy and efficient system to reduce complexity and efforts and provide relevant preferences to reduce rigidity in knowledge provided in terms of course information and skills [11, 14, 21, 29]. As, in Therefore, proposed system provides complete guidance to train users through diverse preferences against each request to lessen the issues during online education.

3. Proposed System

An intelligent system has been proposed here to overcome the issues of virtual personalized preferences during online education, that were identified from literature review. The objective of the proposed system is to virtually assist students and teachers. The students during online education faces several issues such as uploading assignments, solving quizzes and downloading course contents whilst on the other side the teachers toned to deliver lectures, take quizzes and provide contents to students due to their distributed location. The teachers and students both have to take help from different social media forums for better and high standard education but still not able to get accurate and proper solutions to their problems that leads to wastage of time and resources. Some teachers and students who are familiar with the advance technology also need to follow short courses through online training to enhance their skill and perform their online jobs during current pandemic situation. Therefore, proposed system personalized the preferences and predict solutions according to the requirements and interest of the students and the teachers. Thus, proposed system helped those who are new to the advance technologies and those who like to sharpen their scales to compete in modern technological era. The complete overview of proposed system described in Fig.1.

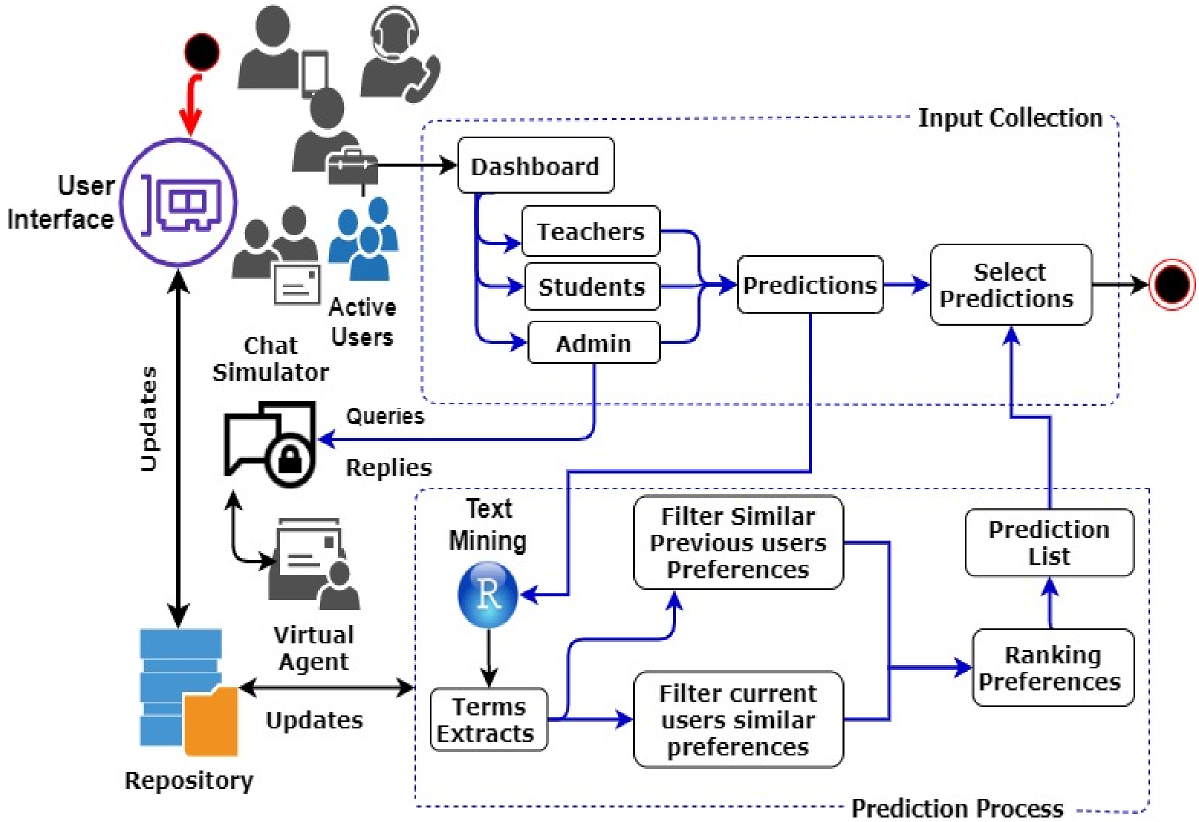

Fig. 1. Proposed System

The proposed system helps to assist virtually teachers and students according to their personalized preferences in crisis situation. Virtually, teachers and students resolve their issues for using appropriate software for online education, solution of problems during online education and appropriate selection of short courses for skill enhancement. The proposed system main steps consists of two main phases i.e. Input collection and the prediction process.

3.1 Input collection

In input collection phase, the input data is collected from different users profiles for their personalized preferences. The student profile interface depicted in Fig. 2 shows the interface that defines background about education, skills and experiences of an individual student. Based on student education and skills the proposed system predicts the personalized preferences for online education to resolve issues of overnight shifting from on campus to online or for guiding to select short courses for improving modern technology requirements. The text mining semantic analysis is used to recommend personalize preferences. Later, the prediction list of solutions relevant to preferences using similar previous and current teachers or students rating or feedback is provided.

3.2 Prediction Process

In this phase, prediction and recommendion lists are generated virtually to enhance online education and to identify appropriate solution for user's online education problems. Virtual agent analyses prediction list based on previous and current similar users selected preferences for relevant issues solutions and feedback after adopting solution. The previous and current user's similarity based on teachers or student's education, skills and requirements. The highest ranked solution predict and recommend to the new request of current or new users. The prediction list after prediction process is depicted in Fig.3. The personalized preferences prediction interface presents the list of courses according to an individual student that improves knowledge by taking course. For this phase we use algorithm 2 and its input depend on algorithm 1.

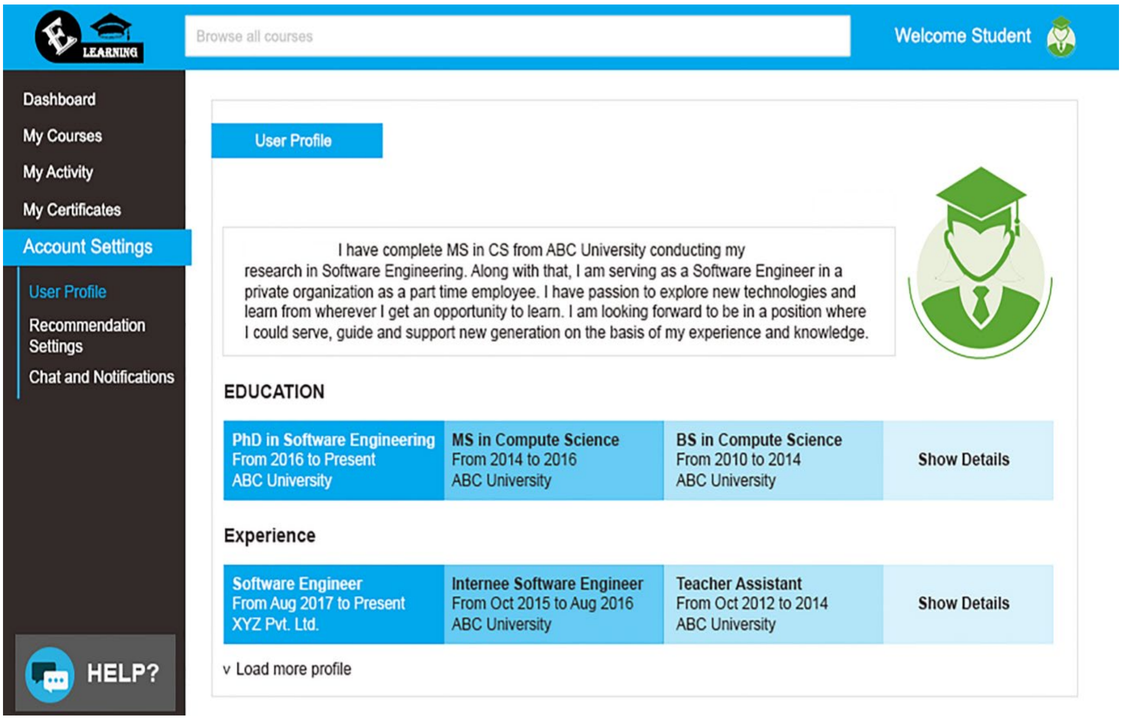

Fig. 2. Student Interface

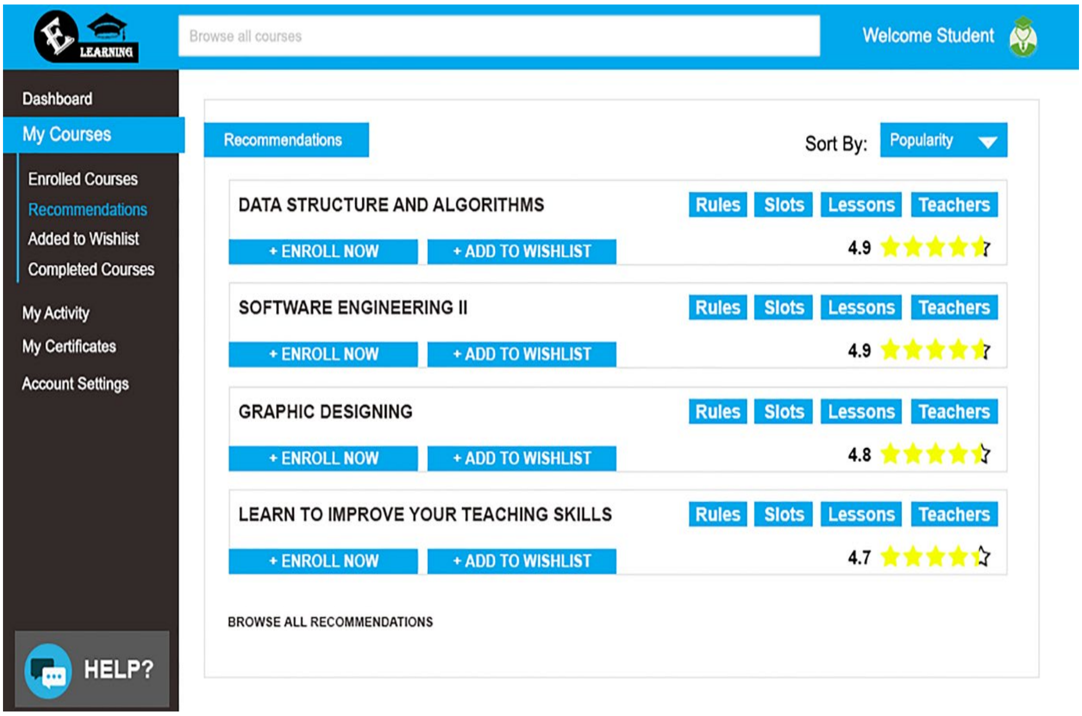

Fig. 3. Personalized Preferences Prediction Interface

3.2.1 Text Mining

In this phase, teacher's or student's requests are semantically preprocessed using text mining methods. For automatic text mining, we used R (R Core Team, 2019) libraries using RStudio (RStudio Team, 2019) for semantic personalized preferences extraction [31–34]. Text mining is a type of data mining and used to understand and find hidden relation in natural language text semantically [31–34]. After the preprocessing the data is stored in a repository. Complete flow of text mining steps is shown in Fig. 4. The reason of preprocessing phase is to reduce lack of information in user provided viewpoints and also to explore or highlight or even identify the hidden relation between the provided information. Table 2 gives an example of term extraction from natural language text to terms of concepts.

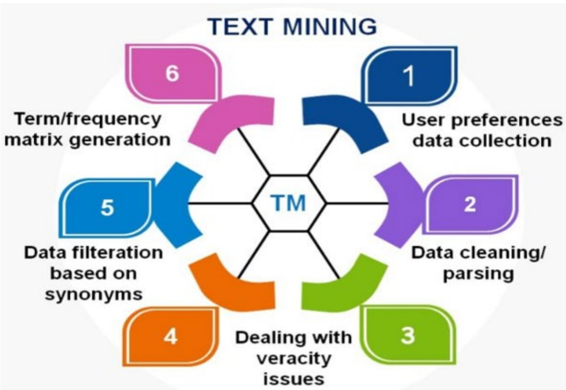

Fig. 4. Text Mining Process

Table 2 Text mining example

Example	Terms of concepts	
	User viewpoint related	**System related**
	Create/open user profile	Display home page

E-learning system requirements for development are;	Student select course/s	Assign User ID
"The user login/signup to management system. The user creates their profiles and submits. Then system display home page with user ID and list of recommended courses. Students select from list with highest ranking."	Submit selection	Courses Recommended List

3.2.2 Ranking Preferences

The ranking preferences based on filtration of previous and current similarity of teachers and student's information. For the filtration skills, experience and qualification of new and current teachers or students is matched with the profile of the former similar students/teachers' experiences based on their semantic perspective analysis during online education. As most of teachers/ student's are new and institutions to technology relevant to online education have shifted from campus education to online education overnight. Therefore, they needed guidance and training for the selection of appropriate online medium for education and virtual assistance for dealing their issues based on personalized perspective or preferences. The most adopted software for online education are Google classroom, Zoom, Microsoft team, Gmail, hangouts and learning management systems of institution. Most of the teachers and students are not familiar with these tools and they face difficulties in adopting and maintaining their education standards. For example, most of institution adopted google classroom as online medium for communication among teachers and students during online education. The teachers upload course contents, assignment, quizzes and handle queries using google classroom. And students have to follows teachers' instructions for contents, assignments etc. and communicate using this medium based on dispersed locations. Thus, teachers/students to enhance activities online education have to get training or resolve their problems while using these technologies. Consequently, they used different social medias and websites for enhancing their skills but not able to get accurate solution according to their problems. For example, the quizzes conduction by teachers in google classroom is problem and after searching from different internet sources solution. The searching of solution wastage of time and not accurately according to preferences. The proposed system extract different solutions according to their personalized preferences about quiz conduction and submission issues. In the pandemic situation also utilize their time by taking short courses or training to enhance knowledge and skills. For example, the teacher/student want to enhance web development skills. Based on their previous qualification and experience analyze and ranked according to current and previous similar users' feedbacks and preferences predict different short courses using algorithm 1-2 to compete in their brighter career. Firstly, these courses extract by analyzing request of teacher/student semantically in the form of terms or required preferences. Secondly, match with current and previous similar students/teachers personalized preferences according to their experiences and viewpoints to predict requirements. Thirdly, sort predicted options according to ranking of previous and current teachers/students.

Algorithm 1: Available Set of previous and current Similar Multi perspective preferences

Input: RF $(Requested\ Preferences)$

P $(Set\ of\ similar\ Preferences)$

Output: MF $(set\ of\ preferences\ similar\ to\ multi\ teacher\ or\ student\ perspective)$

$MF \leftarrow \emptyset$

$\{Set\ of\ similar\ Preferences\}$

$setwd(path)$ $\{setting\ path\}$

$text \leftarrow loadDataFile$

$loadlibraries$

$text2 \leftarrow remove\ puntuation, numbers, stopwords, whitespace, ing", plural\ and\ duplicates$

$text2 \leftarrow change\ case$

$text2 \leftarrow generate\ different\ preferences\ terms$

$\boldsymbol{while}\ till\ end\ of bag\ of\ preferences$

$preferences \leftarrow text2$

$\boldsymbol{end\ while}$

$\boldsymbol{while}\ extract\ preference\ similarity\ matrix\ \boldsymbol{do}$

$p/sm \leftarrow calculate\ preferences\ and\ their\ similarity$

$\boldsymbol{P} \leftarrow p/sm$

$\boldsymbol{end\ while}$

```
16.      for each RF mapping do
17.          If RF_i exists in P then {Select similar preferences relevant to requested preferences}
18.      MF ← RF_i {Save similar preferences accordinmg to new teacher/student request in MF}
19.          end if
20.      end for
21.      Return MF
```

3.2.3 Prediction and Priority

After extracting preferences semantically and filtering according to similarity terms predict list preference (s) with their priority in algorithm 2. For prediction list of preferences extract previous teacher/student preference and priority about similar preferences to classify preferences in accord to highest priority. Therefore, new priority (NP), of predicted preferences with priority is combination of previously prioritized (PP) and currently prioritized (CP) preferences using equation 1.

Equation 1

$$NP = \frac{\sum_{m=1}^{l} V_m}{n} \times CP$$

Whereas,

V represents set of similar preferences; l is set of total number of preferences; n characterises total selected preferences by a specific user, CP represents number of users who recently have chosen a preference Vi. According to Table 3, new sequence of preferences are; P_4, P_2, P_1, P_5, P_3 Using equation 1.

Table 1 Priority of Preferences

Preferences	P_1	P_2	P_3	P_4	P_5
CP	4	3	4	4	5
PP	2	3	1	3	1
NP	8	9	4	12	5

Algorithm 2: Prediction Process

```
Input:  MF (set of preferences similar to multi teacher/student perspective ),
        UP (Previous/current Teacher/student profiles)
Output: PL (set of Prediction List)
1.    PL ← ∅
2.    for PL predicion do
3.                      {Filter Previous Similar Teacher/student }
4.    PS ← ∅                    {PS: Set of Previous Similar Teacher/student}
5.         for each MF of new request in UP
      find similar teacher/student do
6.             if UP select one or more solutions of MF then
7.                                 up ∈ UP
8.                PS ← PS U up {Save up in PS}
9.             end if
10.        end for
11.   {Calculation of MF priority for new request of teacher/student}
12.   NP ← ∅ {NP: New priority of MF}
13.        for each preference MF prioirty do
14.          extract priority of each MF defined by current
             and previous PS then
15.          NP ← priority calculation
16.        end for
17.   Order MF in decending way using NP
18.   PL ← Select highest prioirty requested preferences
19.   end for
20.   Return PL {Prediction List of preference (s) with prioirty}
```

The proposed system assist virtually with the help of virtual agent to resolve issues of teachers/students during online education and guiding teachers/students regarding enhancing their skills and experiences. To validate performance of proposed system research questions used:

- Does the proposed system capable to improve online education?
- Does the proposed system assist appropriately for the selection of personalized environment during online education?

4. Experiments and Analysis

For the evaluation of Proposed system (PS), we have executed a quasi-experiment using two groups i.e. experimental treatment (ET) and control treatment (CT) participants.

4.1 Demographic Information of Participants (Ps)

There were a total of 60 participants including students, virtual agents, teachers and admin managers for conductance of online education during the experiment. These participants may or may not have experience of online education before situating to online education system as described in Table 4. For experiments selected institution shifted from on campus to online education after the impact of current pandemic situation. The Ps of ET were 30 who implemented proposed system (PS), while in CT 30 participants included who used existing method (EM) i.e. existing websites like YouTube, and google without virtual assistance. The recruitment information participants are as follow:

- The participants selection was based on random selection and consists of both male and female individuals.
- The selected students are the undergraduate students of agriculture, mathematics and computer science departments.
- The teachers of these department selected based on their experience in teaching.
- The virtual agents have experience of online education, modern technology and prediction calculation semantically.

Therefore, all participants had different level of experiences, education, expertise and skill. The total period of experiment including from participants selection to output findings were consist of 30 days. Course contents for short courses were selected from different website and information about technology relevant preferences from institution repository they made before experiments after shifting to online education previously.

Table 4 Demographic information

Experience		CT Ps	ET Ps
</> 2 Years	On Campus	10	9
	Online	15	14
</> 3 Years	On Campus	6	7
	Online	10	12
</> 4 Years	On Campus	5	6
	Online	3	2
</> 5 Years	On Campus	6	6
	Online	1	1
</> 6 Years	On Campus	3	2
	Online	1	1

4.2 Experimental Procedure

The experiment was performed in spring session for regular and short courses in selected institution. The objective of proposed system is to predict and recommend list of relevant references to teachers and students according to their multiple perspectives. The prediction list with their priority assists participants to enhance their knowledge, experience and skills during online education with virtual personalized preference assistance. For data collection questioner used as instrument as describe in Appendix A and complete procedure of experimental study described in Fig. 5. Therefore, after the division of participants we applied pre-test and after some essential training to get familiar with proposed system we applied post-test.

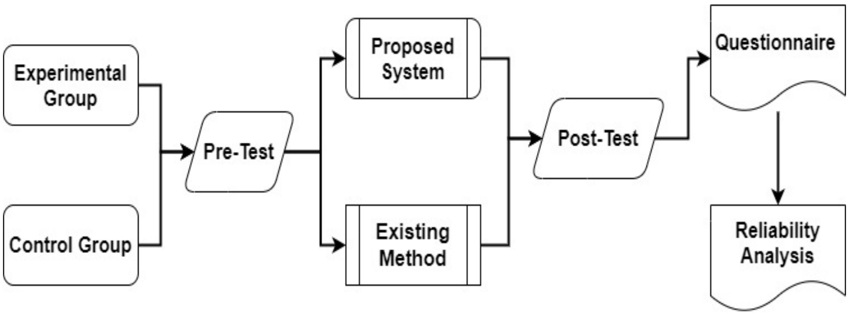

Fig. 5. Experiment Procedure

Then questioner responses were used to analyse after pre and post-tests using statistical methods. The measurement of experiment based on participants satisfaction and novelty effective of proposed system. Thus, for satisfaction of participants we used parametric evaluation which extracted from existing literature i.e. [6, 12, 13, 13, 14, 21, 22, 29]. These parameters described in Table 5 and data collection about these parameters from participants feedback and experience based on questioner.

The pre and post-tests have been designed to investigate effectiveness of proposed system during online education and review of teachers and students after using proposed system. Therefore, after division of participants we assess the previous knowledge, skills and familiarity about technology and reviews about online shifting overnight of participants using questioner. The content of pre and post-test were in the form of videos and slides which were used by the participants for their issues during the use of online software or education or studying short course for skills and knowledge enhancement. These contents saved in the repository and virtual agent helped to access these contents after selection of desire contents. The pre-test and training of participants consist of 5 days, 15 days for learning of contents and 10 days for post-test data collection, results analysis, comparison with pre-test and conclusion. This assessment help to compare results after implementing treatment and improvement achieved. The CT and ET participants have different online and on campus experiences with less satisfaction with shifting to online education. As most of participants not familiar with advance technology, not have access with all online resources, new to technology, face difficulties while communicating with students and teachers due dispersed location and multiple tool involvement. The results of CT and ET participants almost same because most of participants have no or less experience to online education software.

Table 5 Parameters List

S. No.	Parameters	Abbreviation
1	Easy to Understand	EU
2	Less Complex	LC
3	Student Performance	SP
4	Increase Motivation	IM
5	Reduce Effort	RE
6	Learnability	Le
7	Coordination	Co
8	Social Enhancement	SE
9	Personalization	Pe
10	User Satisfaction	US
11	Semantic Information	SI
12	Virtualized Environment	VE
13	Useful Preferences	UP
14	Accurate Recommendations	AR

After applying treatment to ET participants post-test performed on responses. Therefore, before applying treatment of proposed system treatment, provide training to ET about using proposed system and enhance knowledge of CT participants for correct and accurate assessment of post-test. Then compared results of pre and post-tests, to identify difference between pre and post-test values for validating improvement in results after applying treatment.

4.3 Results and Discussion

This section provides a detailed of performing an experiment to evaluate a participant's performance, novelty effect and education quality after applying our proposed system. For analysing data, collected after pre and post-test used SPSS software version 23 as shown in Table 6 and for reliability analysis of data used Cronbach's alpha test as shown in Table 7 used to compare significant difference and reliability analysis results of pre and post-tests.

Table 6

Groups	Ps	Pre-Test		Post-Test	
		Mean	SD	Mean	SD
CT	30	28.1	9.18	36.5	9.55
ET	30	37.6	10.1	60.1	12.05

The mean of CT and ET is 28.008 and 37.6 with standard deviation (SD) 9.18 and 10.1 respectively. The reliability test is acceptable when post-test value is greater than pre-test alpha value. Thus, results for pre-test of CT and Et are 0.69 and 0.76 respectively. Subsequently, post-test of CT and ET are 0.78 and 0.89 respectively. An independent or paired t-test performed to analyse SgD between CT and ET to evaluate hypothesis (H) and significance difference between pre and pot-tests of groups. The p-value (i.e. < 0.05) shows that Ps satisfaction level and performance increases after implementing proposed system. Therefore, reject null H and it indicates ($t = 3.867, p = 0.000$) that participants of both CT and ET possessed a different level of education, experiences, skills etc. Consequently, it also conclude that semantic based predictions in virtualized environment improved selection of relevant personalized preferences and significantly outperform than existing method.

Table 7 Cronbach's alpha

Groups	Ps	Pre-Test		Post-Test	
		t	p-value	t	p-value
CT	30	2.75	0.001	2.989	0.000
ET	30	3.047	0.000	3.867	0.000

For the comparison of dependant (performance, satisfaction level and novelty) and independent variables (i.e. semantic based personalized preferences), we used one-way ANOVA test to verify SgD between CT and ET (see Table 8). The results show that there is SgD between PS and EM with significant value i.e. ($F = 3.750, p = 0.001$) and mean square (MS) values are 141.338 and 134.564. However, the mean score of CT is less than ET, which shows that enhance online course selection process in accord to multi perspectives. The ET showed better achievement in terms of score, which visible in descriptive analysis.

Table 8 Statistical Test

Groups	Sum of Squares	df	MS	F	SgD
Between CT and ET	1978.733	14	141.338	3.750	.001
Within CT and ET	2018.467	15	134.564		
Total	3997.200	29			

In addition to results of questionnaire which prove that PS outperform than EM as shown in Fig. 6 -7 for CT and ET the participants satisfaction level (SL) results. As x-axis depicts satisfaction level of Ps and y-axis shows the number of Ps. The value of satisfaction level of EM or CT group data calculated using questioner instrument to compare results of EM and PS participants. Therefore, Fig. 6. depicted the EM participants scores which calculated using average of questioner data based on five Likert scales for Ps SL after experiment. Thus, SL of teacher, student and manger less than to 65 percent as compared to PS participants which is greater than 65 percent (see Fig. 7).

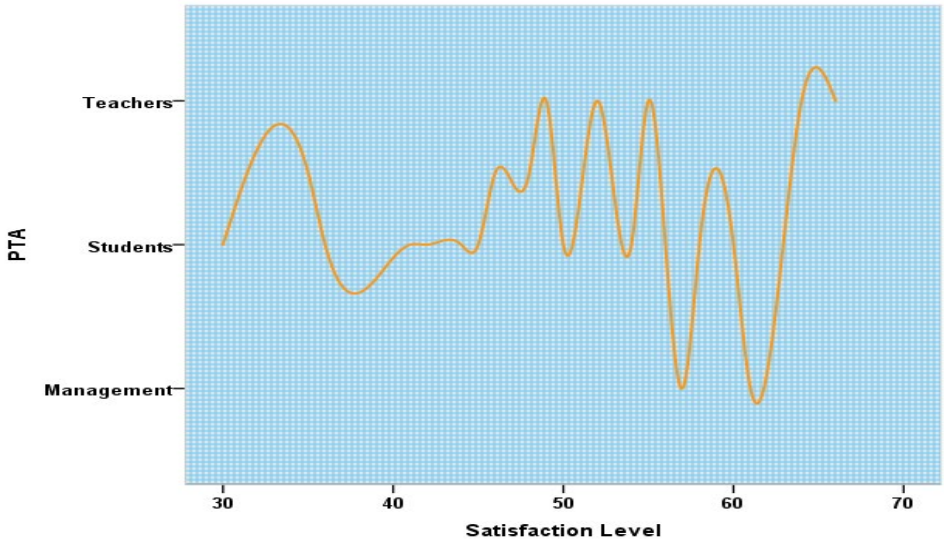

Fig. 6. EM Participants Results

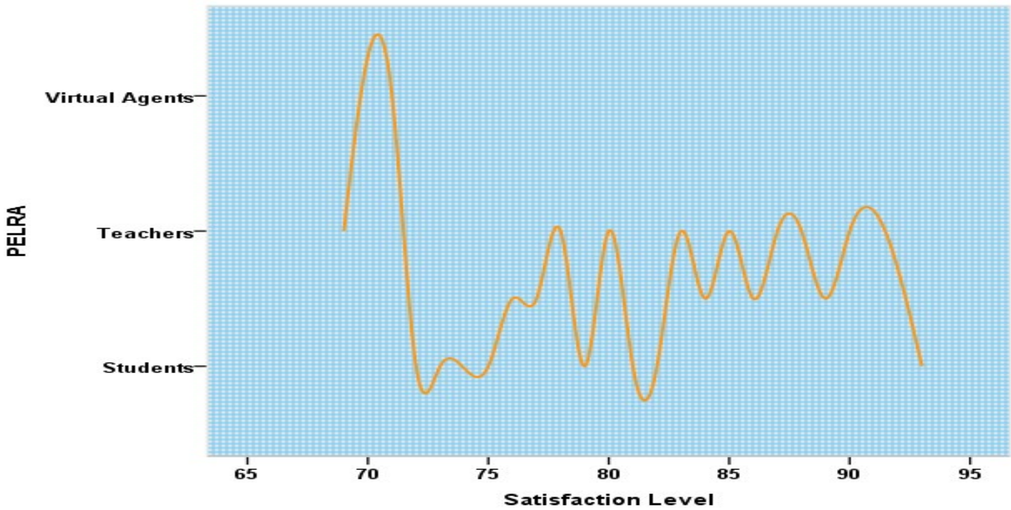

Fig. 7. PS Participants Satisfaction Level

The results of respondent showed that PS improved the online education platform and provide personalized prediction according to multi perspective semantic analysis. However, the proposed system reduced time and efforts involved in recommendation of course list with improved learning quality. The participants also provide an interactive virtualised learning environment/platform for example, if doing class session or during quizzes or examination session feel any query then virtual assistance will help them and resolve their issues. Its makes learning easier according to their interests and requirements in an interactive way especially in case of short courses. Subsequently, from Fig. 8-12 provided results of PS and EM according to each Likert scales as described in Appendix A.

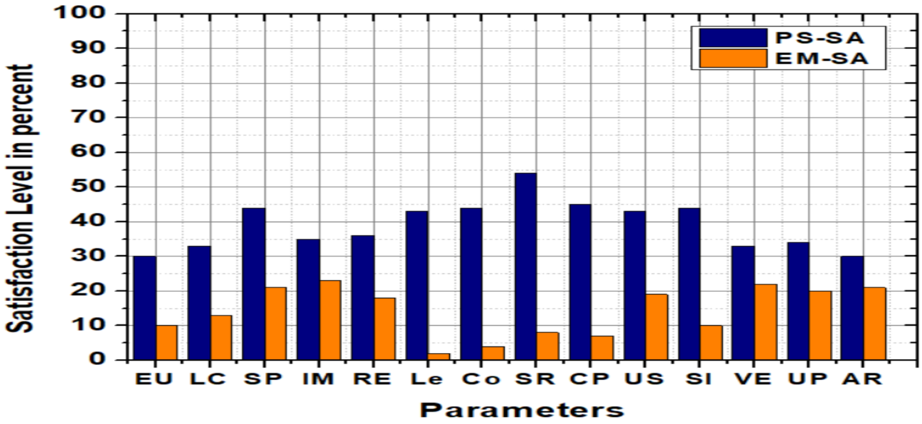

Fig. 8. Parameters Analysis of Strongly Agreed

Consequently, in Fig. 8-12 we discovered out the average of all participants satisfaction level on each parametric comparison listed in Table 4. This depicted that the satisfaction level of all participants who adopted PS is higher than Ps that is based on traditional approach for online learning. Consequently, PS outperforms better than EM and enhance education performance according to highest standard of education.

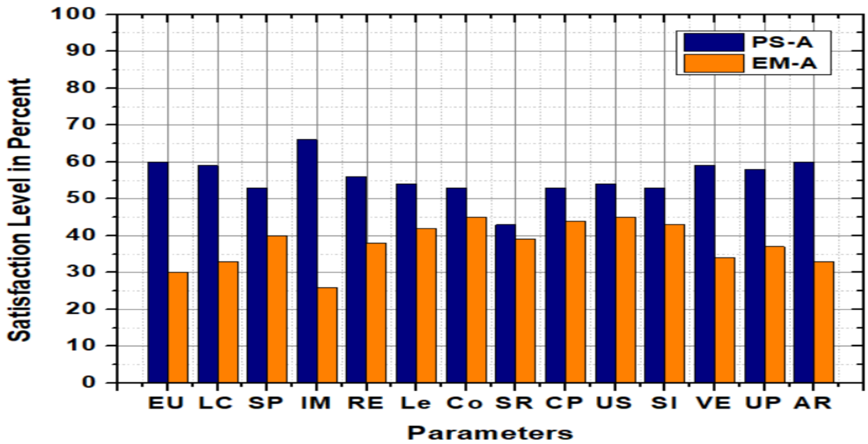

Fig. 9. Parameters Analysis of Agreed

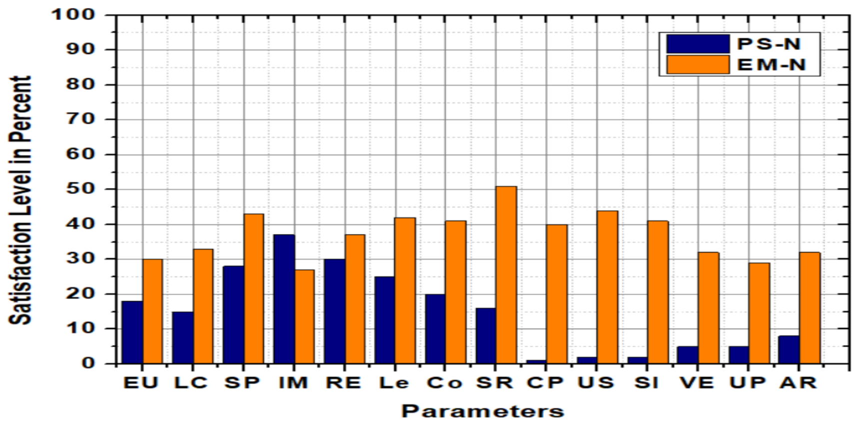

Fig. 10. Parameters Analysis of Neutral

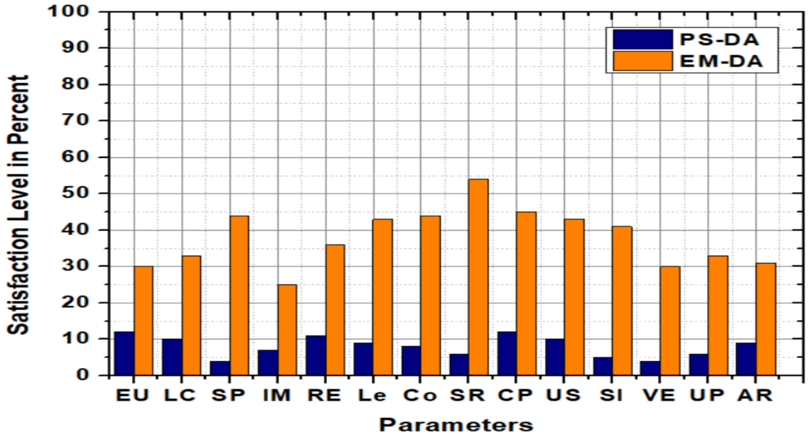

Fig. 11. Parameters Analysis of Disagreed

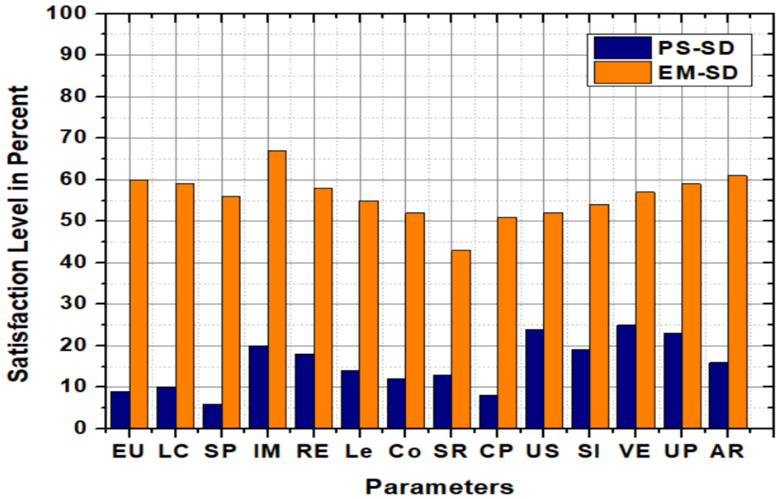

Fig. 12. Parameters Analysis of Strongly Disagreed

4.3 Novelty effect

The ability to detect human learning ability with the involvement of new technology and familiarity with technology contents to memorise easily and better than other method [35–38]. In this research we evaluate novelty effect of PS as compared EM in case of performance, personalized selection, content, flexibility, innovation, interest and learnability according to Ps experiences using data collected after questionnaire. The results depicted in Fig. 11 and identified that using PS participants motivation, knowledge, interest, learning ability and achievements increases as compared to EM.

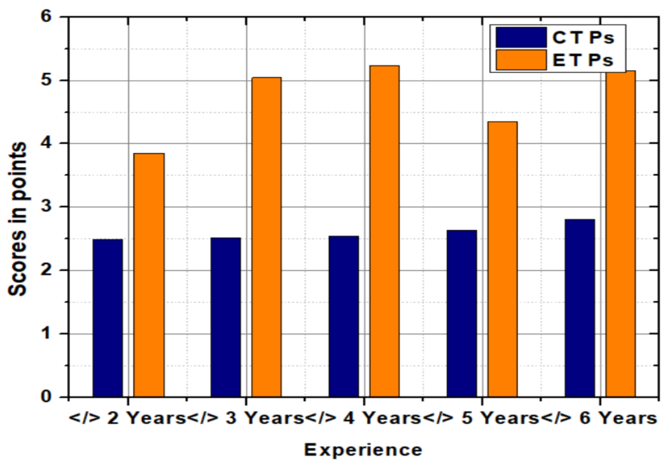

Fig. 11. Novelty effect

4.4 F measure and accuracy

In order to evaluate the success of PS to identify appropriate relevant predictions and selection of personalized preferences used F-measure and accuracy metrices [39, 40]. Accuracy measures exactness in prediction priority personalized preferences using semantic analysis The F-measure used to quantity relationship between predicted preferences and actual relevant predictions. Subsequently, results shows that accuracy of PS and EM are 0.56 and 0.98 respectively and Ps accuracy and F-measure are 0.59 and 0.98 values respectively. The predictions of personalized preferences correctly prescribed to teachers/students according to their requirement and perspective semantically than existing method.

The overall satisfaction level of participants after experiment compared to validate that PS significantly effective and increase satisfaction level of participants as depicted in Fig. 12. The axis y and x describe the SL and participants detail to evaluate performance of each participnats. And results depicted that PS participants have more than 70 percent SL as compared to EM.

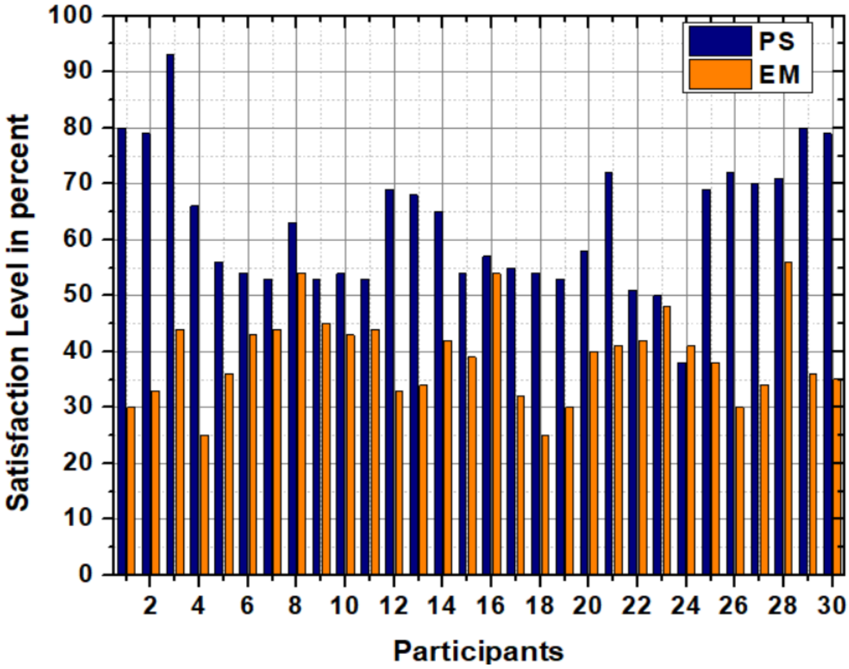

Fig. 13. Comparison of PS and EM

In this study we have examined that preference prediction in e-learning environment improved online learning process by appropriate selection of relevant preferences on the basis of user interest and their preferences in current situation where students and teacher shifted to online education overnight. Therefore, to answer the research question: "Does the proposed system improve e-learning?", the statistics test shows SgD between both proposed system and existing method. Hence, it depicts that appropriate selection of preferences whether to get relevant solution of problem faced during education or short course training selection in virtualized environment with PS improves the performance of student and teacher because they are not feeling bored and fatigue situation during learning. The semantic based multi-perspective preferences selection in VE is vital to increase motivation and enhance skills in recent era. Existing platforms for information searching usually recommend same set of information, irrelevant and redundant information to multi perspective preferences of users at one time and without virtual assistance which hinders their personalized preferences process. Use of semantic based and virtual assistance-based recommender system not only increase users' motivation but also helps in improving skills to meet educational or organizational requirements. Learners and tutors found it interesting to learn and enhance their professional/educational skills with the idea that they could find interesting and relevant courses without any interruption in virtual environment. In addition, learners' and tutors' felt more confident and competent because it helped them in learning and teaching syntax-based courses according to their own and market needs.

During experiment we have identified that the learners of control group get bored when they have selected irrelevant course from the available courses which in return causes fall in student's performance as compared to previous performance or their results. During study sometime, their slot has assigned to other student or at the time of quiz the interface may not working properly and there was no online agent to help them. While in case of PS same situation occurred and then resolved with the help of virtual agent and with recommendation system there is a less chance of irrelevant selection of courses. Hence, overall all the participants of experimental group whether they are learner, teachers, and virtual agents, they have the higher satisfaction level then the participants of control group. As parametric analysis depicted that the users of PS have the satisfaction level of more than 50 percent as compared to traditional approach users whose satisfaction level was less than 50 percent.

It has been noted that participants of both groups have achieved the different satisfaction level during different courses recommendation process. In traditional method usually, some list with limited courses options and is same for all learners and not considered the multiuser perspective and learner must select relevant courses whether it belongs to their interest or not. During course session there is a lack of virtual assistance at run time which loses the interest of learners. They may not be able to achieve better results. While PS mitigates the online learning issues and increase the interest of learner. It not only enhances their skill and knowledge but also motivate them to give high ranking to course to encourage other relevant learners. The study evaluation results are promising with certain limitations. The experimental implementation was for short period of i.e. for one-month period. For longer period implementation, results may affect the interest of learner regarding course material and learner performances. Therefore, the study has been extended to assist tutors or material designers to enhance the syllabus and material according to latest knowledge and requirements to validate the quality of recommendations and performance of both learners and tutors.

5. Conclusion and Future Work

The present paper has proposed the semantic and virtual agent-based recommender system named PS to provide multi perspective personalized recommendations that assist learners/tutor for searching and choosing relevant learning/teaching courses according to their interest and preferences in real learning environment with the help of VA. The PS considers multi perspective for selecting relevant interesting learning material to enhance and improve skills, knowledge and online learning process of both learners and teachers. Moreover, there are two noteworthy implications of the PS i.e. first of all, to assist learners and teachers in finding suitable advance courses which enhance their knowledge and skill in accordance to their interest and requirements. Secondly, PS deals with online queries of users to reduce coordination and ambiguity among users and team for high quality education. The outcomes validate that proposed system techniques have significantly improved the skills and achievements effectively and had enhanced the learning performance (i.e. more than 90 percent) as compare to other traditional techniques. Future study will focus on enhancing the PS for updating syllabus and learning material dynamically and validate the performance of both learner and instructor to improve the quality of online education environment.

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Appendix A: Questioner

The appendix provide information about questions used for data collection during experimental study. Thus, questioner divided into three sections.

Section 1: Demographic Information of Participants					
Name:					
Qualification:					
Teacher:	Student:		Virtual Agent:		Manager:
Gender:	Male		Female		
Age:	</> 18 Years	</> 25 Years	</> 35 Years	</> 45Years	</> 60 Years
Experience:	</> 2 Years	</> 3 Years	</> 4 Years	</> 5 Years	</> 6 Years
On Campus:					
Online:					

Then participants fill section 2 to provide review about proposed system performance and satisfaction level. Hence section 3 used to identify proposed system novelty effect. For section 2 and 3 used five liker scales used selected i.e. 1= Strongly Agreed (SA), 2= Agreed (A), 3= Neutral (N), 4= Disagreed (DA), and 1= Strongly Disagreed (SD). The participants ranked them from 1 to 5 points ranking.

Section 2: Performance and Satisfaction Level						
No.	Questions	Scaling				
		SA	A	N	DA	SD
Q1	Does proposed system provide easy to understand and manage education standard?					
Q2	Does proposed system is suitable and less complex to improve online education?					
Q3	Does proposed system improve student performance during online education period?					
Q4	Does proposed system increase motivation of teacher/students for online education?					
Q5	Does proposed system reduce effort during online education?					
Q6	Does proposed system provide a personalization mechanism to support teachers/students in order to facilitate interactive online education current pandemic situation?					
Q7	Does proposed system have capability to enhancing coordination among teachers and students using virtualized environment?					
Q8	Does the social enhancement increase using proposed system in order to formulate new method?					

Q9	Does proposed system increase llearnability by providing personalized preferences based on multi perspective ultimately enhance overall standard and quality of education?					
Q10	Does user satisfaction facilitate teachers and students to enhance their skills, experience and knowledge?					
Q11	Does proposed system extract efficiently Semantic Information for accurate any complete personalized preferences?					
Q12	Does proposed system useful and to implement and trained teachers anf education in virtualized environment?					
Q13	Does the preferences predict by proposed system useful preferences during online education?					
Q14	Does proposed system identify relevant and accurate recommendations for higher performance?					

Section 3: Novelty Effect						
No.	Questions	Scaling				
		SA	A	N	DA	SD
Q1	Does proposed system methodology new experience for you?					
Q2	Does proposed system capable for identifying relevant and unique solution for personalized preferences in modern way?					
Q3	Does you get accurate preferences prediction list semantically using proposed approach?					
Q4	Does proposed system easy to use and implements desire preferences?					
Q5	Does proposed system provide new way after text mining and participants previous behavior?					
Q6	Does proposed system able to reduce gaps among theory and practices to implement in real scenario?					
Q7	Does proposed system capable to manage and increase information semantically as compared to existing methods?					