Heliyon 9 (2023) e17863

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Smart education system to improve the learning system with CBR based recommendation system using IoT

Veeramanickam M.R.M [a,b], Manisha Sachin Dabade [c], Sita Rama Murty P [d], Ratnaprabha Ravindra Borhade [e], Shital Sachin Barekar [f], Carlos Navarro [g], Ulises Roman-Concha [g], Ciro Rodriguez [h,*]

[a] Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India
[b] Department of Software Engineering, Universidad Nacional Mayor de San Marcos, Lima 15081, Peru
[c] Department of Information Technology, Walchand College of Engineering, Shivaji University, Sangli, India
[d] Department of Artificial Intelligence & Data Science, Vishnu Institute of Technology, Bhimavaram, Andhra Pradesh, India
[e] Dept. of Electronics and Telecommunication, MKSSS's Cummins College of Engineering for Women, Pune, Maharashtra, India
[f] Dept. of Computer Engineering, MKSSS's Cummins College of Engineering for Women, Pune, Maharashtra, India
[g] Faculty of System Engineering, Universidad Nacional Mayor de San Marcos UNMSM, Peru
[h] Department of Software Engineering, Universidad Nacional Mayor de San Marcos UNMSM, Peru

ARTICLE INFO

Keywords:
Internet of things
Smart learning techniques
Artificial intelligence
Recommendation system

ABSTRACT

Over the last few years, the research fields of intelligent learning systems have been improving the process of learning systems. Smart Tutoring System-(STS) applications have been used in e-learning. The results signify the importance of the learner's engagement in customizing a model. The design outcomes of this IoT-based personalized learning system purely work on the audience's learning requirements, their keyword search, their learning experience levels, proficiency level of subjects, and the type of the course being taught. Students spent an average of 25.67 h accessing textual materials weekly, 27.4 h accessing video assets weekly, and similarly 6.5 h accessing visual learning materials. The research analysis part concludes participants' percentage of learning as per evaluations assessment, which increases whenever the outcome analysis comes with Case-Based Reasoning classifiers-CBR based search model. The findings displayed significant differences before and after learning case by case for every learner as per chosen topic and quiz assessments: 42.57% of the students responded before learning the first question assessments whereas 74.82%, of the students responded, after completion of learning from online resources based on their choice with CBR. Recommendation Model Analysis discussed root means square error-RMSE lies from 10% to 20% for 550 students group size. The RMSE result is 24% for a size of 1600, which is low performance compared to other group sizes. This study focuses on the STS recommendation model for the slow learner group to identify required learning from various online resources.

* Corresponding author.
E-mail addresses: veeramanickam@chitkara.edu.in (V. M.R.M), msdabade2017@gmail.com (M.S. Dabade), sitaramamurty.p@vishnu.edu.in (S.R.M. P), rrborhade11@gmail.com (R.R. Borhade), sheetal.barekar@gmail.com (S.S. Barekar), cnavarrod@unmsm.edu.pe (C. Navarro), nromanc@unmsm.edu.pe (U. Roman-Concha), crodriguezro@unmsm.edu.pe (C. Rodriguez).

https://doi.org/10.1016/j.heliyon.2023.e17863
Received 6 December 2022; Received in revised form 18 June 2023; Accepted 29 June 2023
Available online 3 July 2023
2405-8440/

1. Introduction

Nowadays, learning plays **an important** role in the growth and progress of every individual qualification and achievement. Plenty of online learning materials are available for teaching and learning every student. In such a scenario, many numerous e-learning web platforms are available to learn the complete topics and the demanded courses throughout the world. The authors' work is on the importance of how to personalize learners' growth and progress with the data analysis learning model.

A system of intelligent tutoring for the integration of the Internet of Things (IoT) can lead to more engaging and efficient products. Smart Tutoring System-(STS) applications make a difference to the inferior outcomes of those learning and working on a non-personalized template platform. Students can be assigned to learn according to their learning profile, which can be accessed through either web applications or handheld mobile applications. The content delivery approach was designed using multimedia resources, together with subject domain web application learning resources like industry experts' white papers and top speakers' blog postings, for better content delivery for STS.

This work studies the importance of personalizing learners' growth and progress with data analysis learning as per the CBR smart learning system. Many terms are used nowadays along with e-learning, like learning life long, i.e. constant learning at every stage of their professional growth concerning rapid changes in working culture due to covid19, adaptations of ICT platforms with continuously evolving and new age technology. Our traditional learning in the classroom is changing rapidly due to various reasons, such as lack of smart learning and no personalized learning and others. Adopting a new way of distance mode of online learning with the help of an e-learning platform is quite easy to reach everyone, as per their needs and demands, and its shown in Fig. 1.

Smart tutoring system-STS which enhances learners' progress based on intelligence is added to personalize learners' requirements as per tracking of their independent learning rather than traditional learning. To improve STS based on smart learning, thus, working on blend learning. Blend learning is a platform that provides help to learners in the form of AI. It is a real-time intelligent tutor with embedded sensor data with machine learning analysis. It can be used for personalized and adaptive learning. The scope of STS has been envisioned to be extended to include not only the designing of instructional materials but also the provision of recommendations concerning content and skill development plans for students. This work presents an STS based on CBR data analysis of learning techniques coupled with blended knowledge of engineering techniques that supports learners' competency analysis through adaptive planning and realistic content recommendation in various domains such as language education, programming, maths, and science [1, 2].

Data computation of STS-based learning is discussed with different learning models with certain steps involved are:

- The objective of learner's
- Finding required resources with correct search terms
- Technology evaluation of ICT
- Data processing &user skill integration with learned and new learning resources
- Consolidation and learners' knowledge illustration [3].

The main focus is to understand the importance of learning and the interest in their page navigation movements, chosen topics with search terms words, their eye movements, blinking, visual information, focusing on particular content in learning. The most important thing is to analyze how these different learning resources help to create an impact on learners' outcomes. In this study, quiz assessment is done before and after this analysis for the smart recommendation.

Providing learners with knowledge and instruction is the main goal of online learning platforms. Providing an opportunity for individuals to use their newfound talents and deepen their understanding of a given topic. Students, however, may differ in terms of

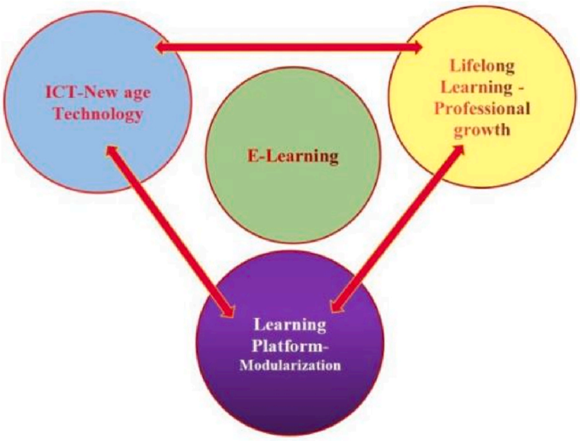

Fig. 1. E-Learning focus area features.
Source: Veeramanickam (2023).

their past knowledge. Therefore, it is crucial to create adaptive learning systems to maximize the effectiveness and motivation of the learning process. This modification should occur independently of the instructor, the course's author, or the teacher. The important goal of e-learning working platforms is to give students access to knowledge and real-world experiences that will help them develop their skills and deepen their understanding of a certain subject. However, various students may have different demands, motivations, or prior knowledge. For learners to be efficient and engaging as possible in a variety of learning models, it is crucial to build adaptive learning systems. Such changes for adopting the smart learning model are independent of the listed available courses, the STS design model and the instructor. The word cloud of research elements is majorly for the STS model based on knowledge sharing, development of applications, intelligence learning model, Questionnaire for assessments, and many more, focusing on the adaptable learning recommendation system with the CBR model.

2. Literature review

Literature work related to STSs discussed various ways of adopting a smart system to support and enhance students' learning environments. The user's efficiency level of learning improves by searching keywords giving corresponding exact learning resources of text and also web search, which increases utilization of the video resources. Many of the users are in the age range of 20–27 years, which is 60% of the overall users actually for YouTube. This research is useful in terms of learners personalizing characteristics for enhancing the way of learning, suggestions and skill integration, diagrams and textual data sharing whenever learners find searching learning content [4,5]. IoT Application based on usage of various sensors: Smart kitchen appliances with a sensor like knives use IoT to monitor motion and sense when the blade is chopping; such as robotic hands, which prevent user error. Load cells are embedded in smart handles to chop fruit and meat design boards to provide more safety shown in Fig. 2. An acceleration sensor detects blade movement whenever any objects are placed under the blade tool in the board using area [6]. An internet data center server transmits data for smart IoT applications [7].

The IoT setting supports device-to-device communication, local area network and wireless connection-orientated protocols. The IoT environment consists of a personalized recognition system and provides device-to-device end communication and network connectivity. The IoT permits machines to acknowledge things, people, and object movement in response to given requests, knowledge sharing, and collaboration.

The authors discussed industrial agriculture, logistics [9], communication, safety [10], thus academic sectors will be highly beneficial in their working capabilities. It is utilized in existence to boost the training experience, encourage learners, and boost the potency level of outcomes [11]. The IoT can be used in daily life in things like motion sensors, home security systems that discover motion, causing signals such as associate in nursing automatic off-switch requests, medical monitors for patients and elderly, and data sharing transmission [12,14]. Let us focus on a few important literature studies in terms of Smart tutoring systems with IoT features. The different applications of e-learning are listed below in Table 1. Some of the major aspects like adaptivity of the smart learning model, intelligent system with reciprocal learning, Competency level of student learning, CBR experts system are given in Table 1.

IoT-based STS is designed based on the concepts theory of Alessi. et al. Instructional teaching model [17], with help of Cognitive teaching and learning for multimedia from Mayer [18]. The smart teaching and learning tutor model is used for design based on Nwana [19]. And also, the CBR model is utilized for the artificial domain of the application platform. As mentioned in Table 1, the author discussed many models of smart STS from the early different prototypes applied by Mokmin. et al. [20,21].

The authors worked on the importance of teaching assistance among all participants with the MOOC Platform, Clubbing all related queries together to assist the students. This work focused on how to address students' queries with the help of teaching assistant tools for MOOC forums. Overall lag for personalized learning phases [30] Learning objects is focused more on effective retrieval from the given repositories. This recommendation system is useful in terms of course design with usage of machine learning models and context-aware learning objectives, a smart system for very easily searching and designing customized courses design curricula with existing learning objectives. But lagging suggesting relevant learning resources only focused on the design of learning course [31].

The authors stated the importance of Recommender Systems with Semi-supervised Learning using machine learning but didn't work on e-learning applications for smart tutoring recommendation models [33]. In this work, authors implemented a cost-efficient model with IoT for the best approach to IoT applications based on QoS with the help of a whale optimization algorithm to produce good throughput and energy consumption [34,36]. In this work, the authors implemented a smart library recommendation model educational organization but did not work on the e-learning tutoring model. The smart library application is a different learning phase recommendation model [35,37]. Thus, authors worked on CBR to enhance learning experience through adding new cases as per

Fig. 2. IoT Model Conformation [8].
Source: Chalermdit, J.et al. (2019)

Table 1
Literature study for IoT-based STS Model.

Name of the Authors, Number of Authors	Origin & Year of Publication	Title-Article	Type of Source	Research Design	Target Population	Proposed Framework	Major Themes
Péter Négyesi, Ilona Oláhné Téglási, Réka Racsk (3)	Korea 2021	Pros & cons of e−learning environments from an adaptivity Perspective [13]	Convergence Education Review - Researchgate	Adv. and Disadv. of E− learning platform	Researchers and Students	No	E-Learning
Zlatkovic, M Ilic1, N Denic, S Jovkovic. (4)	Serbia 2021	Designing and validating the questionnaire used to measure the attitude of students E-learning [21]	IOP Conference. Series: Materials Science and Engineering	Kaiser-Meyer-Olkin, Bartlett's Test Sphericity, Cronbach's Alpha	Students	No Validity and Reliability of the Questionnaire	E-Learning, ICT
M Mavani (1)	India 2010	Blending Intelligent and Reciprocal Tutoring Systems [15]	(ICWET '10). ACM	Evaluation and Analyzer Agent, LMS	Researchers	Blended Architecture	E-Learning, RTS
Jiragorn Chalermdit, Prachyanun Nilsook, Panita Wannapiroon (3)	Thailand 2019	Graphical Tutoring System Using the IoT to Develop the Competency of ES [8]	iJOE Journal	IOT, STS	Researchers	Graphical Tutoring System with IOT platform	E-Learning, IOT, STS
Jay E,. Aronson (2)	USA 2003	Expert Systems [16]	Elsevier	CBR Model	Researchers	Expert System -CBR	E-Learning
Swati Shekapure and Dipti D. Patil (2)	Pune, India 2019	Enhanced e-Learning Experience using Case based Reasoning Methodology [38]	Science and Information (SAI) Organization, Publication House.	CBR Model	Students	Expert System -CBR	E-Learning
A. Flores, L. Alfaro and J. Herrera (3)	Peru 2019	Proposal model for e-learning based on Case Based Reasoning and Reinforcement Learning [39]	IEEE Explore EDUNINE 2019-Conference	CBR and Reinforcement Learning	Students	Expert System -CBR	E-Learning

simulation with new learning history which is able to acquire changes in incremental dataset in further classification [38]. Whenever there are no similar CBR cases, a q-learning model based on Reinforcement Learning is used for finding and choosing a learning sequence [39,40].

3. Proposed system

In online learning, web-based searching plays a vital role in finding relevant important learning resources for students which are described using various computing and theoretical models. Some of the important steps are listed below: [31,32]:

- Personalized learning objectives are based on the importance of the learner's requirements.
- Utilization of search engines for finding required learning resources by searching with the help of different inputs like text, images, and video.
- Case-based personalization with data processing and knowledge sharing on the basis of resources learning.
- Knowledge sharing among all learners subsequent of every new learning cycle.

The important objective of this research work is to find out how online learning resources create an impact on learners' outcomes based on the learning phase. Using a case-based reasoning approach helps every learner, hence finding the best possible learning phase for every individual. The web-based searching model is always useful in terms of assisting learners to find out their learning subject topics from online resources. Students can collect the required information for knowledge gained by learning through available online resources like trainers' videos, and multimedia content of subject notes via a web searching model.

This research investigates the attention paid to searching for information online by learners as they navigate and users' eye movements using sensors. This research study is completed to understand the importance of capturing web resources for learners' knowledge is quantified. Using the various sensors helps to boost the user's responding time, optional selection, and sensitivity. The learners spend more time looking at videos and less time studying pictures.

3.1. Objectives of model

This section explained about the recommendation model for analyzing the learnable searching online case by case using CBR for the recommendation model. The model helps learners to match relevant text information mapping and video learning resources. The sensors are useful in recording the learner's page navigation and eye movement. All the step-wise procedures listed below are how to function for this objective.

1. Collecting and storing student users searching learning resources with eye movement tracking and keeping records of all log data information in file storage for every user available in the database.
2. For all learners who visited online learning, their records must be maintained to track and trace them to figure out their learning phase with the CBR model.
3. Improvising a Tutoring system with relationships between learning data utilized which are new to them apart from their already known topics, can be manipulated with sensors.
4. Keeping records of the search words sequence used to differentiate between personalized and non-personalized to work on a smart STS model.

3.2. Multiple modern features updates for E-learning platform

There are various important factors post-COVID-19 due to (WFH work-from-home) given to many workers throughout the world. This leads to giving high priority towards uninterrupted internet facilities and data speed, smart device mobile configuration, the most effective hardware equipment with good compatibility factors and reliability, …etc. Therefore, the very basic important factors is how to preserve such knowledge transfer in covid time duration in order to address all difficulties in terms of redesigning educational curriculum.

In gamification of digital platform are given multiple design features importance, like blending model, learners personalized learning phase, and advancement of technology enhancement rather than only resources facilities [22]. Hence, this signifies progress of learning experiences for every user with minimal down time of networking, most effective communication, knowledge transfer, multiple learning assessments, learning bit by bit small topics, learner engagements as shown in Fig. 3 [23].

The relationships among multiple entities in learning environments are very important, like concepts presentation, learning by video lectures, audio clips of podcasts, tutorial text data, etc. [24,25], The students' engagements in terms of interactive teaching, learning content with interesting presentation, ensue with sets of surprise quick small assessments are shown in Fig. 4 [26,27].

Data repository which stores different learning resources in e-learning from multiple teaching and learning tools. In all virtual classrooms, it is important to use such learning data storing repository [28,29].

The design and development of STSs (STS) with machine learning prediction of CBR have improved the learning process in recent times. The integration of STS with IoT given in Fig. 5 architecture has significance in terms of highly engaging and effective outcomes. STS products have the potential to be more interactive, engaging, and effective as a result of the integration with the Internet of Things. The STS platform is studied and developed with multimedia learning theory, design, tutoring, and IoT data analysis of learning resources. The proposed model is used to analyze learner sensor data tracking and computation for CBR. This helps in finding out matching cases as per existing learner cases to suggest for new CBR case study. In recommendation, data analysis for text and video

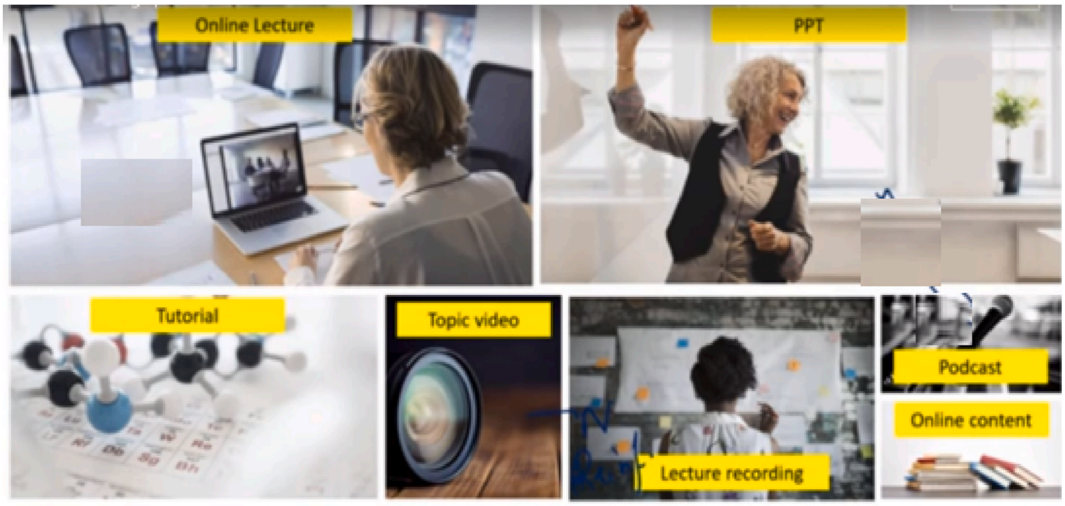

Fig. 3. Faculty content in various utilization of digital learning.
Source: Veeramanickam (2023)

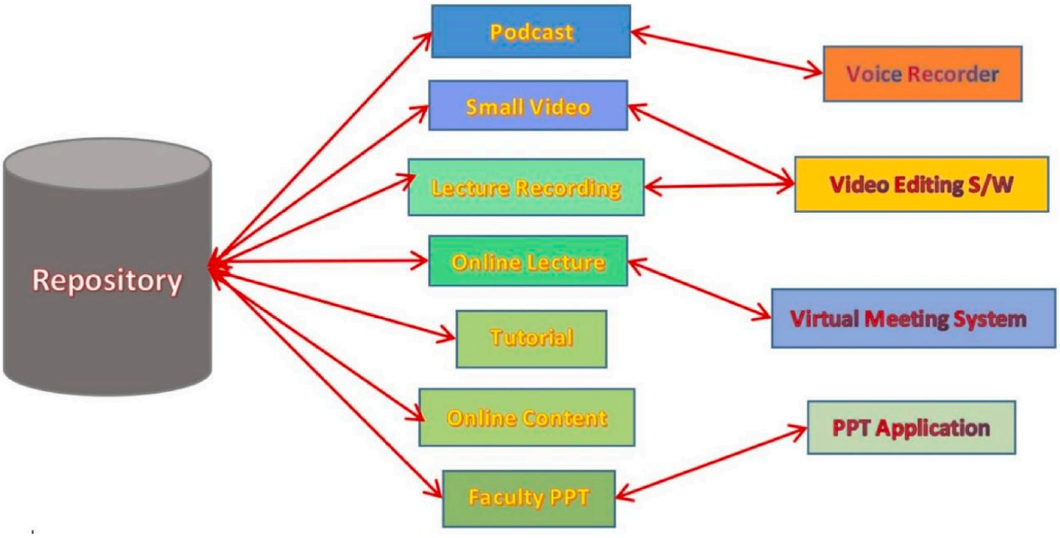

Fig. 4. Topics based relationship between concept content and LMS with different application tools.
Source: Veeramanickam (2023)

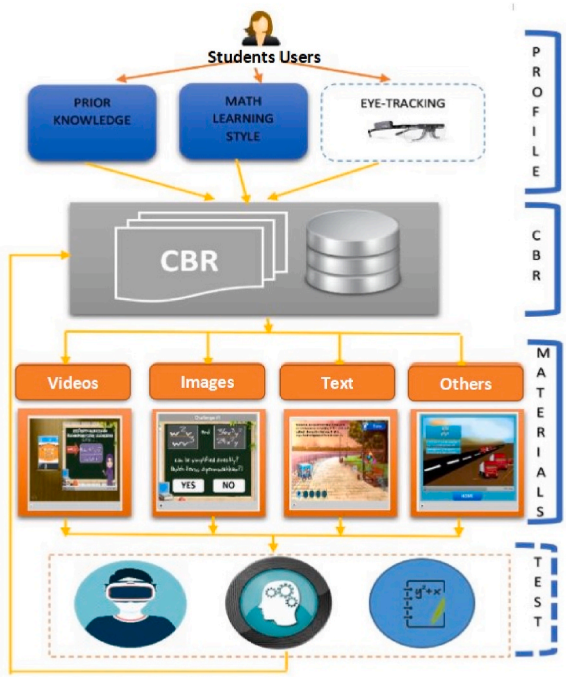

Fig. 5. Architecture model - STS based CBR analysis.
Source: Veeramanickam (2023).

resources with certain functional steps like: data collection, recording of data logs, processing collected data, finding and mapping operations based on CBR results work [16].

The proposed model is used to analyze for users through IoT-based sensor data tracking and computation analysis of those data passed on to CBR to help find out matching cases as per already learned users' records to support new learner users. This online resource of text and video search analysis with certain steps are comprised like: data collection, recording of data logs, processing those data, and finding and mapping operations based on CBR results [16].

3.3. Step-wise procedure- method

In this research study working methodology with a three-step procedure as listed below: the first is data collection, the second is processing data analysis, the third is finally mapping for research analytics insight. In this section of data collection from concerned end users, oral consent is taken for data analysis and research purposes as approved by the ethical committee "Doctoral Research Programme" led by the Dean of Alpha Cluster (department of CUIET) from Chitkara University, Punjab, India, which includes documenting of data collection, utilized without mentioning user identity for privacy purpose and consent was obtained from all participants for this experiments.

Step 1. Data collection

1: Evaluate the user's earlier skill sets and knowledge.
2: Performing online searches based on keyword sequence.
3: Mapping online resources of video and text information.
4: Evaluate users after learning resources.

Step 2. Processing the data

1: Extracting the words based on the usage of a learning concept.

2: Using sensor data for collecting user tracking records for text, image, and video resources.

3: Extracting the word usage after learning post-knowledge evaluation.

Step 3. Define and find mapping operations based on CBR results

1: Removing the unwanted word search after processing CBR.
2: Performing learning path matching to personalize or non-personalize in STS
3: Construct final result suggestions and learning resources for the students.

The proposed work can address the following points in this research work:

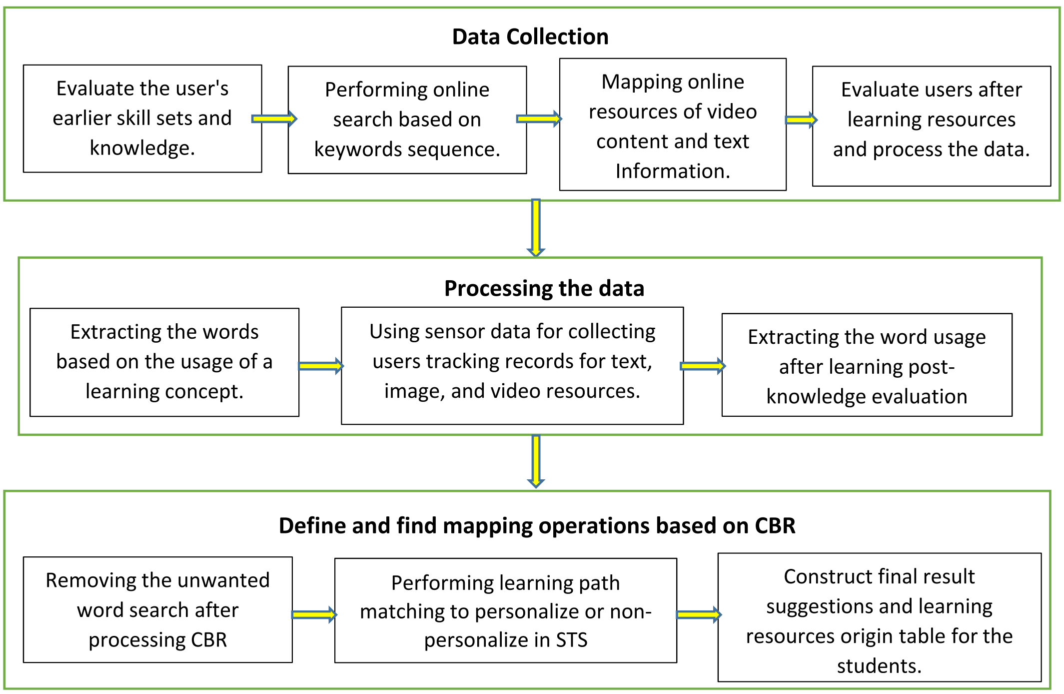

Fig. 6. Resources processing model architecture source: Veeramanickam (2023).

Q1. How many times searches are done by the student user?
Q2. How exactly to figure out the mapping relation between every case in CBR?
Q3. How many words sequence given are useful outcomes for learned users?
Q4. What is the average session duration of every successful learner?

Finally, results suggest that learners search for terms as per their learning phases. The results outcomes are related to search terms as per Fig. 6 for every new learner to search for required notes from online search case by case for CBR with word originality in origin table output.

3.4. Students learner information

The research work of students on user data analysis with simulation of 500 users from different platforms in the initial stage, later increased to 1600 users and subject domains are participated. The learner's structure is tabulated in Table 2, and the *mean*∞ and *standard deviation* σ of various groups are listed in Table 3.

On the overall average, requesting users to use the internet for a minimum of 25 h every week. The learner's platform familiar whenever using the online search platform is calculated with a scale range from 1 to 5 which increases usage of performing level experience. Then, based on the prior learner's subjects domain, skill set and knowledge were analyzed with CBR based STS shown in Table 2

3.5. CBR for IoT-based STS personalized model

Learners Task Evaluation Pre and Post-learning of Online Resources. The students were asked to learn and complete this fundamental of their subject's domain topics to answer a few questions in terms of assessment evaluation and to answer such questions at the end of every topic learning. Every learner's performance was analyzed after a certain learning period. CBR provides a very important approach for building suggestions which assists decisions made based on existing past case records.

Subject-wise data assessments as per Fig. 10 which is discussed in detail for different groups size as per Fig. 11. A Learner profile is based on three content resources: video, text and images, as per Fig. 5 explains its importance.

- Learner Profile: Visual information, Audio data, Kin-esthetic data with textual, image and video
- Learning resources: Video based learning, Chart visuals, Audios podcast, Simulation study, Textual resources
- Test assessments analysis: Quiz 1 and 2 Assessments

Unlike the Nearest Neighbour model, store training data tuples as data points in Euclidean space for computing outputs. In this case-based reasoning classifiers storing data as cases in database data records to find problem solutions to solve in terms of new case. CBR working functionalities explained further. CBR will first determine whether an identical training case already exists before classifying a new case. If one is discovered, the case's companion solution is returned. The CBR will look for training examples given in Fig. 7 with elements that are comparable to those with the new case if an identical case cannot be discovered. These practice instances may theoretically be thought of as the new case's neighbors. This entails looking for sub-graphs that are similar to sub-graphs within the new case if cases are represented as graphs. To offer a solution for the new example, the CBR tries to merge the solutions of the nearby training cases. Backtracking to looking for alternative solutions may be necessary if compatibility with the individual solutions occurs.

4. Results discussion

This research work was conducted for 500 learners at stage one and later, 1600 learners stage further by using sensors in various subject domains, and the student performance was evaluated. Hence, it is important to understand pre and post-learning of resources content topic-wise with different sets of question sets for STS. These results indicate that experimentally, on average, 34.55 h are spending time duration every week with: 7.53 for online searches with e-learning platforms.

The weekly number of accessing count for learning materials is given in Fig. 8. For every learning content, the accessing time duration every week is calculated. Fig. 8 displays plotted results for weekly learning vs learner access count. On overall average, the students spent 25.67 h content accessing textual data, 27.45 h accessing video learning materials, and then images for 6.5 h accessing shown in Fig. 9.

For different groups of users, two evaluation questions of quick MCQs assessments are done for data study analysis. The first MCQs

Table 2
Structure of the student learners.

Science	15%
Programming	40%
Mathematics	10%
Electronic	10%
Computer Science	25%

Table 3
Different learning concept groups for μ and σ

Subjects	μ	σ
Science	1.75	1.92
Programming	1.10	1.85
Mathematics	1.72	1.74
Electronic	1.33	1.60
Computer Science	1.94	1.96

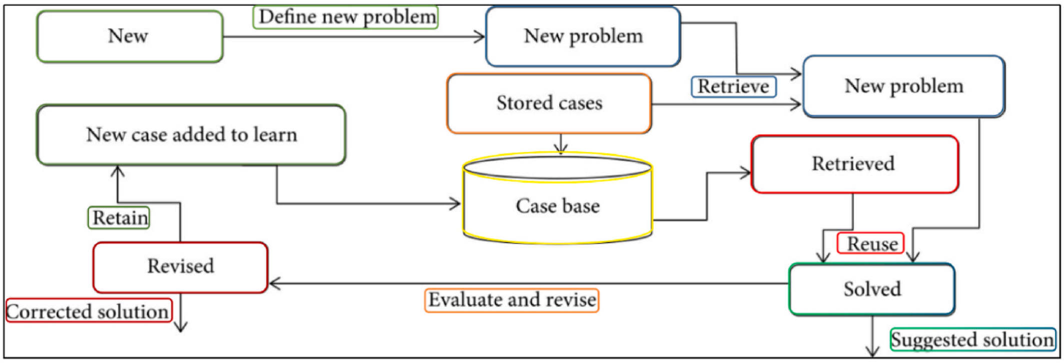

Fig. 7. CBR-based STS working model.
Source: Veeramanickam (2023)

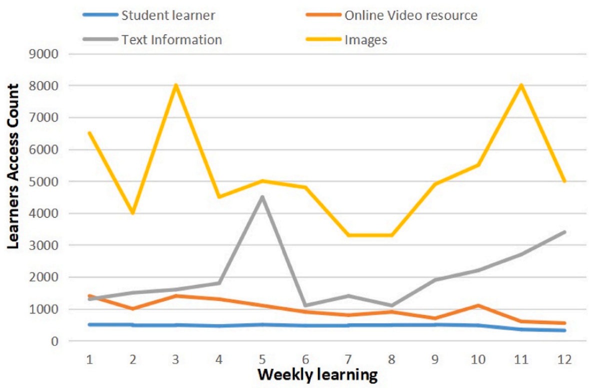

Fig. 8. Weekly access count of learning resources.

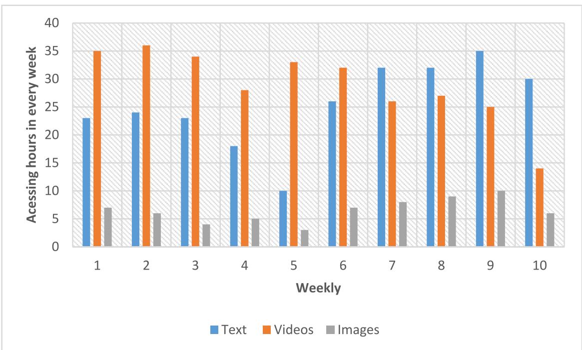

Fig. 9. Weekly accessing time duration among learners for resources.

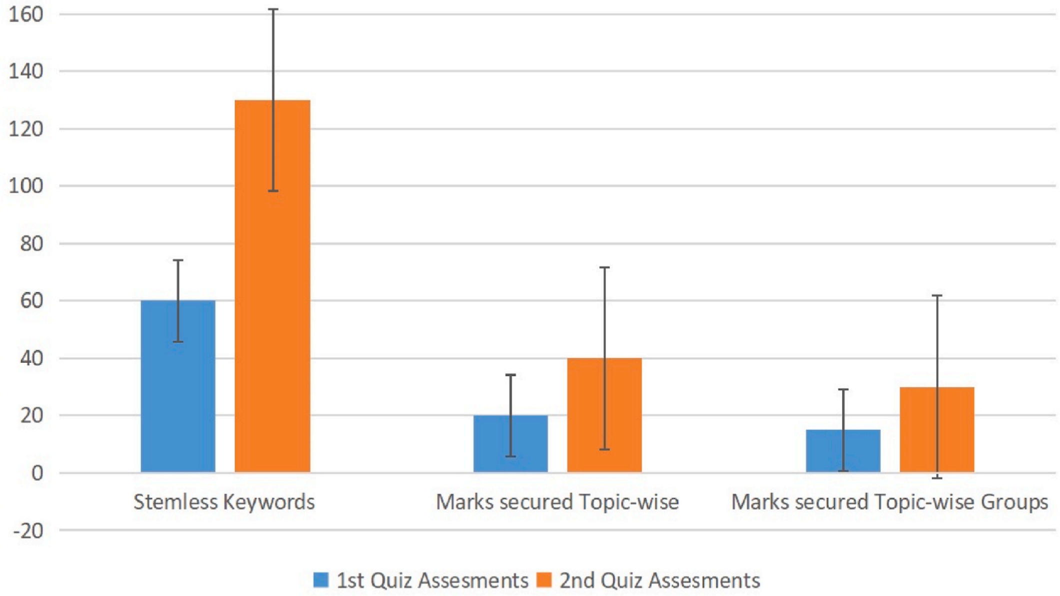

Fig. 10. Stemless words scored concepts and scored concepts topic-wise.

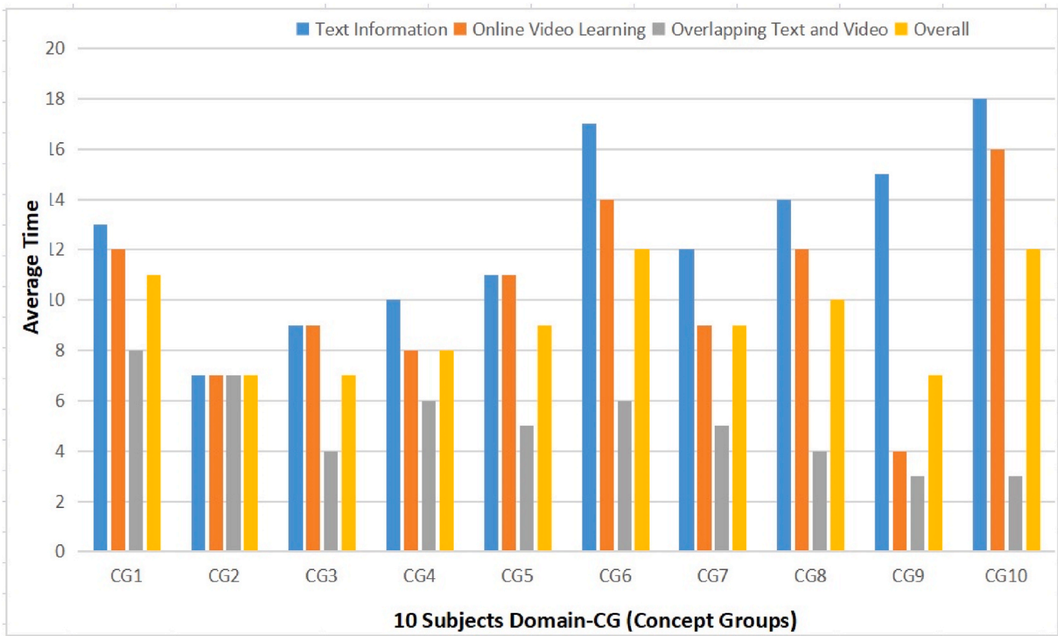

Fig. 11. The mean number of words from Q2 retraced to fixated text or video transcripts.

question is completed earlier the web search understanding and the second MCQs question is completed at a later stage. These count scores among different entities– the number of stemless words, the number of scored concepts, and the number of concept groups were increased gradually only whenever the students attempted the quiz question after web searching.

The user participants' percentages are addressed with a two question quiz, based on the 10 defined subject domain concept teams utilized, which are plotted in Fig. 10. This analysis concluded that participants' results in terms of evaluation assessments questions 1 and 2 increased only whenever the learners attempted quizzes after completing keyword searching. It is found in this analysis that 43.67% of the learners are not addressed properly for the first question before completing learning and searching, and 75.32% are well addressed for the second question after the search and learning.

The expected results outcomes of the countable word search from questions 1 and 2 are displayed above in Fig. 11. This analysis concluded as overall average word counting corresponded with related terms of text data, and video streaming, and overlapped either text data or learning video, and the final results of resources are obtained as 12, 13.33, 5.16, and 14.25, respectively.

4.1. Recommendation Model Analysis

The main operational functionality of data collection from the learners, processing that information in terms of search terms, word usages and finally mapping for search table with the help of the CBR model. This flow of work is to figure out expected outcomes for impact created for the learning phase with every individual for smart recommendation systems. The outcomes increase after every learning phase for learners. The main focus is on this recommendation system which is defined clearly in the proposed objectives methodology.

$$\text{Recall calculation} = \text{number of valid learners count} \ / \ \text{X learners} \tag{1}$$

$$\text{Precision calculation} = \text{number of valid learners count} \ / \ |\text{L}| \tag{2}$$

$$\text{Ranking calculation} = \sum_{a \in \text{X learners}} \text{rank (a)} \ / \ |\text{X learners}| \tag{3}$$

The RMSE calculation is based on $\sum i = 0$ to n, then p (a,u) subtracted with the rate (a,u) which is divided by n with the final result square root. This recommendation smart system data processing outcome is evaluated with the following metrics like precision calculation, rank values, and recall calculations. All results are evaluated using the above three equations (1) to 3) to find the mean value of μ and Standard deviation SD - σ; which are listed below in Table 4 respectively.

The study found the best performance measures from the smart recommendation system which are compared with other working systems displayed in Table 4. These study results for RMSE measured with different sets of students group sizes like 280,330, 370, 430, 480, and 550 are given in Fig. 12. The graph displayed below for RMSE lies in the range of 10%, 20% as per the student group is less than 550 and the maximum value of RMSE is 24% whenever the student group size reaches 1600.

The recommendation table size and the precision calculation are plotted in given above line chart Fig. 13. The final Smart STS working model based on CBR gives a good performance of precision of 26% as per the given learners size 100.

The precision and recall measured values for different learning group sizes like 280, 450, 550, 750 and 1000 are plotted in the given above graph Fig. 14, and the proposed CBR-based STS recommender table obtains good performance results.

5. Conclusion

This research studied about the importance of enhancing learners' skill sets with the help of an STS based CBR model. This design model contributes to integrating personalized learning by providing enriched multimedia content, effective usage of e-learning platforms, an effective means of learning resources search, and finally, learned topics assessments pre and post-personalized STS based CBR learning. To understand the impact of learning based on time spent on textual, image and video content by learners, which leads to knowledge sharing contribution with the personalized STS model. The students spent an average of 25.67 h accessing textual materials, 27.4 h on video access for learning, and 6.5 h accessing visuals. The majority of student learners choose to learn from video content instead of other resources. Whenever students take the quiz after completing STS based CBR web search using stemless keywords leads to an increase in the number of concepts that were scored and an increase in number of concept groups gradually from earlier parameters. This result study analysis concludes that the participants' percentage of taking the quiz increased whenever the students took the assessment following their web search. Only 43.67% of the students responded to the first quiz before finishing their web search, whereas the findings show that 75.32% responded to the second question after finishing their web search with STS. According to the analysis, the average word count for texts, videos, overlapped texts or videos, and all other resources are 12, 13.33, 5.16, and 14.25, respectively. The STS model has been evaluated to understand the pupils who learned using personalized learning materials outperformed those who used non-personalized learning materials. Based on the audience's learning needs, the nature of their search queries, their level of expertise in learning subjects, their competency level, and the kind of chosen course, all these are taken into the STS design of this learning system. The CBR-based STS working model is useful in terms of perpetual multiple sessions for content searching in the online web environment. The important key role in understanding the students' knowledge acquisition with the help of STS for the betterment of every learner is measured. The range of outcomes in percentage is increased only after every student's learning phase completion. The RMSE graph displayed in the above figure gives the range of 10% to 20% for the 550 students group size, and 24% is the maximum value of RMSE for a group size of 1600. This research study gives a better understanding of the

Table 4
μ and σ Comparison with different Working Models.

Working Model	Ranking Values (μ) (σ)		Recall Calculation (μ) (σ)		Precision Calculation (μ) (σ)	
Collaborative Filtering-CF	0.590	0.004	0.250	0.005	0.020	0.021
Clustered Intelligent based CF	0.074	0.001	0.353	0.007	0.090	0.013
CBR based STS Model	0.078	0.002	0.350	0.009	0.092	0.014

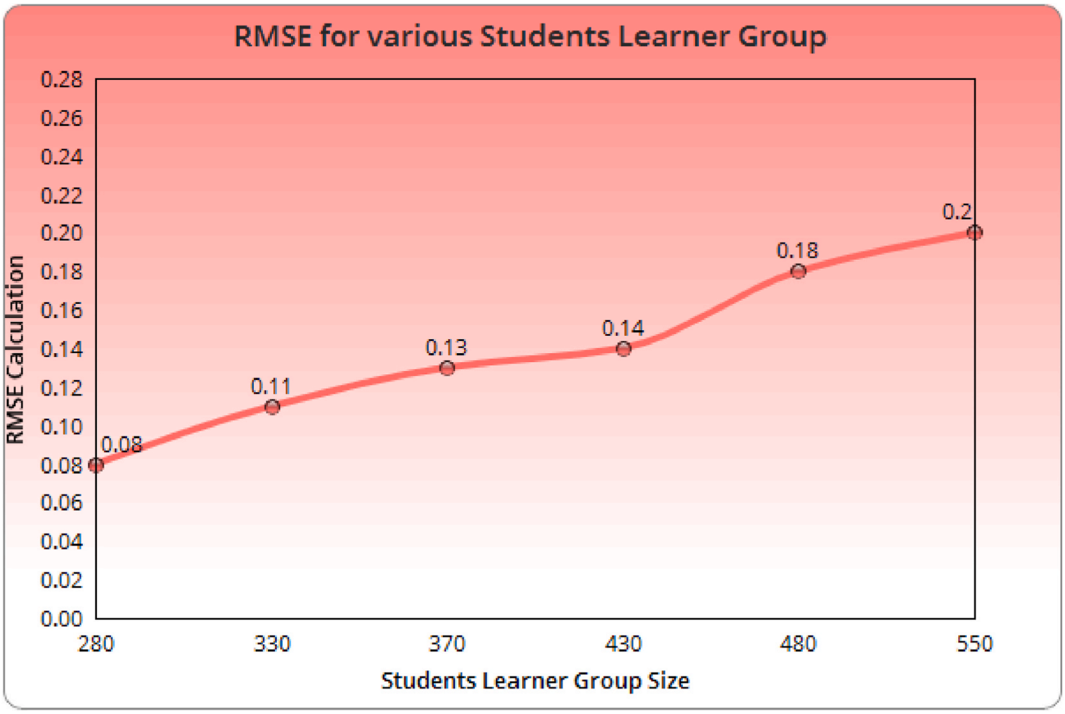

Fig. 12. RMSE for various Students Learner Group.

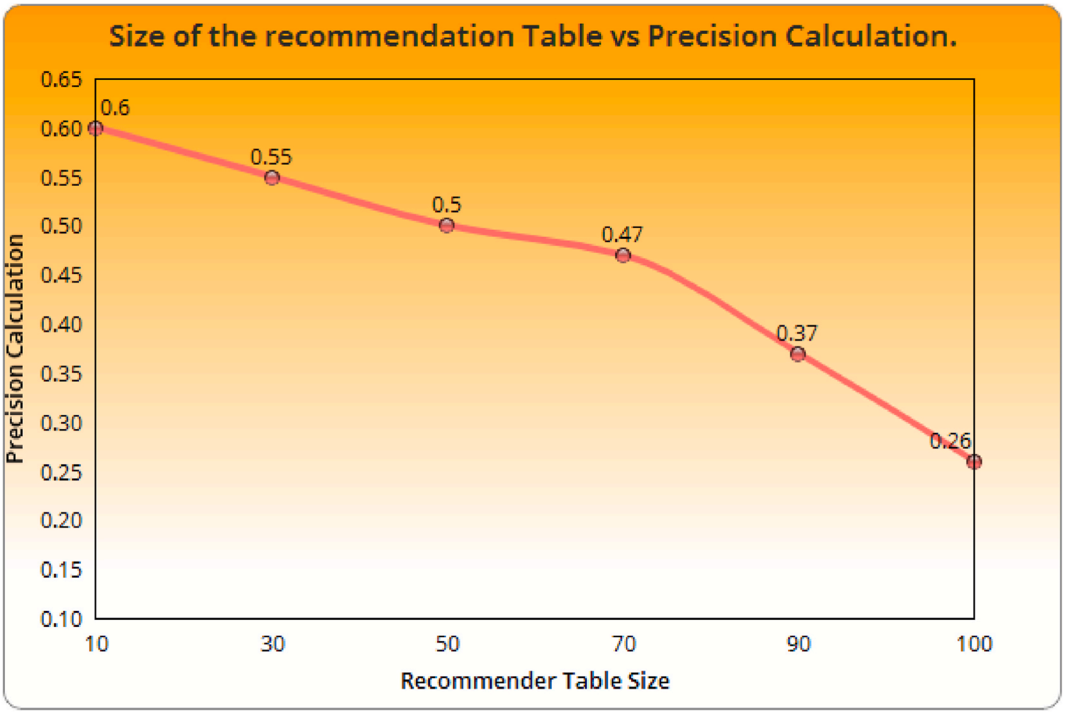

Fig. 13. Size of the Recommendation Table vs Precision Calculation.

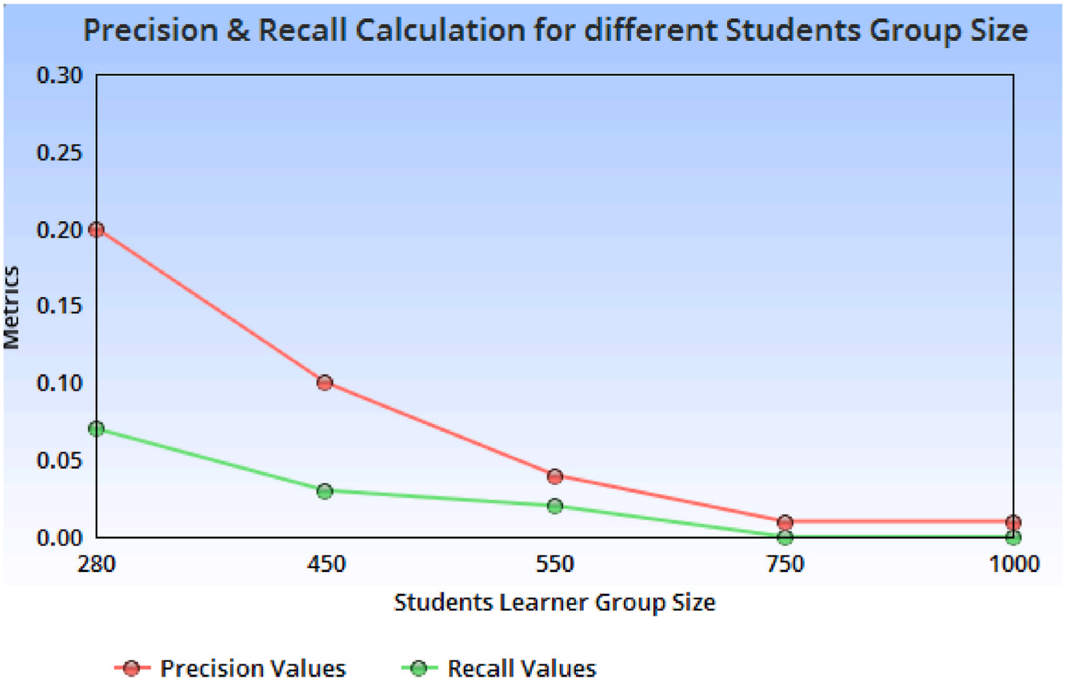

Fig. 14. Precision and Recall Calculation for different Students Group.

smart STS recommendation working model for the slow-learning student group in identifying the required learning materials for the various online learning platforms.

Funding

The authors declare that funding for the research and publication of this article is provided by Universidad Nacional Mayor de San Marcos (UNMSM) according R.R.N° 00898-R-17.

Author contribution statement

Dr. Veeramanickam M.R.M.: Conceived and designed the experiments; Wrote the paper.
Ciro Rodriguez R: Conceived and designed the experiments.
Mrs. Manisha Sachin Dabade: Performed the experiments.
Dr. P. Sita Rama Murty: Performed the experiments.
Carlos Navarro: Analyzed and interpreted the data.
Ulises Roman Concha: Analyzed and interpreted the data.
Dr. Ratnaprabha Ravindra Borhade: Contributed reagents, materials, analysis tools or data.
Dr. Shital Sachin Barekar: Contributed reagents, materials, analysis tools or data.

Data availability statement

The data that has been used is confidential.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] N. Zhang, G. Biswas, N. Hutchins, Measuring and analyzing students' strategic learning behaviors in open-ended learning environments, Int. J. Artif. Intell. Educ. 32 (2022) 931–970, https://doi.org/10.1007/s40593-021-00275-x.

[2] S. Brand-Gruwel, I. Wopereis, Y. Vermetten, Information problem solving by experts and novices: analysis of a complex cognitive skill, Comput. Hum. Behav. 21 (3) (2005) 487–508, https://doi.org/10.1016/j.chb.2004.10.005.

[3] S. Brand-Gruwel, I. Wopereis, A. Walraven, A descriptive model of information problem solving while using the internet, Comput. Educ. 53 (4) (2009) 1207–1217, https://doi.org/10.1016/j.compedu.2009.06.004.

[4] R.E. Mayer, Cognitive theory of multimedia learning, in: R. Mayer (Ed.), The Cambridge Handbook of Multimedia Learning, Cambridge University Press, 2014, pp. 43–71, https://doi.org/10.1017/CBO9781139547369.005.

[5] R.E. Mayer, Using multimedia for e-learning, J. Comput. Assist. Learn. 33 (5) (2017) 403–423, https://doi.org/10.1111/jcal.12197.

[6] A. Whitelock-Wainwright, N. Laan, D. Wen, D. Gašević, Exploring student information problem solving behaviour using fine-grained concept map and search tool data, Comput. Educ. 145 (2020), https://doi.org/10.1016/j.compedu.2019.103731. Article 103731.

[7] L. Salmerón, A. Sampietro, P. Delgado, Using internet videos to learn about controversies: evaluation and integration of multiple and multimodal documents by primary school students, Comput. Educ. 148 (2020), https://doi.org/10.1016/j.compedu.2019.103796. Article 103796.

[8] J. Chalermdit, P. Nilsook, P. Wannapiroon, Analysis of an intelligent graphical tutoring system using the internet of things (IoT) to develop the competency of embedded systems, Int. J. Online Biomed. Eng. (iJOE) 15 (4) (2019) 98–110, https://doi.org/10.3991/ijoe.v15i04.9511.

[9] N. Ahmad Uzir, D. Gašević, W. Matcha, J. Jovanović, A. Pardo, Analytics of time management strategies in a flipped classroom, J. Comput. Assist. Learn. 36 (1) (2020) 70–88.

[10] T. Käser, D.L. Schwartz, Modeling and analyzing inquiry strategies in open-ended learning environments, Int. J. Artif. Intell. Educ. 30 (3) (2020) 504–535.

[11] O. Zlatkin-TroSTSchanskaia, J. Hartig, F. Goldhammer, J. Krstev, Students' online information use and learning progress in higher education—a critical literature review, Stud. High Educ. 46 (10) (2021) 1996–2021, https://doi.org/10.1080/03075079.2021.1953336.

[12] S.K. Janahan, M.R.M. Veeramanickam, S. Arun, K. Narayanan, R. Anandan, S.J. Parvez, IoT based smart traffic signal monitoring system using vehicles counts, Int. J. Eng. Technol. 7 (2.21) (2018) 309–312.

[13] Négyesi, P., Téglási, I. O., & Racsko, R. Pros & cons of e-learning environments from an adaptivity perspective. Convergence, 7(2).

[14] N. Bharathiraja, M. Shobana, S. Manokar, M. Kathiravan, A. Irumporai, S. Kavitha, The smart automotive webshop using high end programming technologies, in: Intelligent Communication Technologies and Virtual Mobile Networks, Springer, Singapore, 2023, pp. 811–822.

[15] M. Mavani, Blending intelligent and reciprocal tutoring systems: a dynamic approach, in: Proceedings of the International Conference and Workshop on Emerging Trends in Technology (ICWET '10), Association for Computing Machinery, New York, NY, USA, 2010, pp. 704–707, https://doi.org/10.1145/1741906.1742069.

[16] Jay E. Aronson, Expert systems, in: Hossein Bidgoli, Encyclopedia of Information Systems, Elsevier, 2003, 2003, pp. 277–289. ISBN 9780122272400.

[17] S.M. Alessi, Trollip, Multimedia for Learning:Methods and Development, third ed., Allyn and Bacon, Boston, MA, 2001.

[18] R.E. Mayer, Computer Games for Learning : an Evidence - Based Approach, MIT Press, Cambridge, 2014.

[19] H. Nwana, STSs: an overview, Artif. Intell. Rev. 4 (4) (1990) 251–277, https://doi.org/10.1007/BF00168958.

[20] N.A.M. Mokmin, The Development and Evaluation of Personalized Learning Material Based on A Profiling Algorithm for Polytechnic Students in Learning, Universiti Sains Malaysia, 2016.

[21] N.A.M. Mokmin, M. Masood, The effect of four differentiated multimedia learning materials in algebra learning, in: ICERI2015 Proceedings, IATED, 2016, pp. 8518–8524.

[22] R. Kaur, A. Garg, P. Kaur, Case study: student's response towards online learning in Engineering Education during COVID-19 Pandemic, J. Eng. Edu. Trans. 34 (3) (2021) 2349–2473.

[23] M.R.M. VeeraManickam, M. Mohanapriya, B.K. Pandey, S. Akhade, S.A. Kale, R. Patil, M. Vigneshwar, Map-reduce framework based cluster architecture for academic student's performance prediction using cumulative dragonfly based neural network, Cluster Comput. 22 (1) (2019) 1259–1275.

[24] M.R.M. Veeramanickam, N. Radhika, A Study on Educational Games Application Model in E-Learning Cloud System, International Conference on Information Communication and Embedded Systems (ICICES2014), 2014, pp. 1–5, https://doi.org/10.1109/ICICES.2014.7033842, 2014.

[25] A. Whitelock-Wainwright, N. Laan, D. Wen, D. Gašević, Exploring student information problem solving behaviour using fine-grained concept map and search tool data, Comput. Educ. 145 (2020), https://doi.org/10.1016/j.compedu.2019.103731. Article 103731.

[26] L. Salmerón, A. Sampietro, P. Delgado, Using internet videos to learn about controversies: evaluation and integration of multiple and multimodal documents by primary school students, Comput. Educ. 148 (2020), https://doi.org/10.1016/j.compedu.2019.103796. Article 103796.

[27] M.R.M. Veeramanickam, P. Ramesh, Analysis on quality of learning in e-Learning platforms, Adv. Eng. Software 172 (2022), 103168, https://doi.org/10.1016/j.advengsoft.2022.103168.

[28] R. Dutta, S. Malhotra, A. Kumar, A. Parashar, S. Sharma, Effect of cognition on e-learners as compared to traditional learners during Covid19, May, in: AIP Conference Proceedings, vol. 2357AIP Publishing LLC, 2022, 080010, 1.

[29] M.R.M. Veeramanickam, N. Radhika, A smart E-learning system for social networking, Int. J. Electr. Comput. Eng. 4 (3) (2014) 2088–8708.

[30] T. Wang, H.N. Cheng, Z. Cai, The Linguistic Differences in Concept Conveying in English and Chinese xMOOC Forums, Heliyon, 2022, e12551.

[31] P. Delgado, Ø. Anmarkrud, V. Avila, L. Altamura, S.M. Chireac, A. Pérez, L. Salmerón, Learning from text and video blogs: comprehension effects on secondary school students, Educ. Inf. Technol. 27 (2021) 5249–5275. List, A. Strategies for comprehending and integrating texts and videos. Learn. Instr. 2018, 57, 34–46.

[32] S. Tahir, Y. Hafeez, M.A. Abbas, A. Nawaz, B. Hamid, Smart learning objects retrieval for E-learning with contextual recommendation based on collaborative filtering, Educ. Inf. Technol. 27 (6) (2022) 8631–8668.

[33] A.H. Khan, J. Siddqui, S.S. Sohail, A survey of recommender systems based on semi-supervised learning, in: International Conference on Innovative Computing and Communications: Proceedings of ICICC 2021, vol. 3, Springer Singapore, 2022, pp. 319–327.

[34] M. Ghobaei-Arani, A. Shahidinejad, A cost-efficient IoT service placement approach using whale optimization algorithm in fog computing environment, Expert Syst. Appl. 200 (2022), 117012.

[35] A. Simović, A Big Data smart library recommender system for an educational institution, Libr. Hi Technol. 36 (3) (2018) 498–523.

[36] M. Ghobaei-Arani, S. Asadianfam, A. Abolfathi, Deploying IoT services on the fog infrastructure: a graph partitioning-based approach, Software Pract. Ex. 52 (9) (2022) 1967–1986.

[37] Beulah Christalin LathaChristudas, E. Kirubakaran, P. Ranjit JebaThangaiah, An evolutionary approach for personalization of content delivery in e-learning systems based on learner behavior forcing compatibility of learning materials, Telematics Inf. 35 (3) (June 2018) 520–533. Elsevier.

[38] Swati Shekapure, Dipti D. Patil, Enhanced e-learning experience using case based reasoning methodology, Int. J. Adv. Comput. Sci. Appl. 10 (4) (2019), https://doi.org/10.14569/IJACSA.2019.0100428.

[39] A. Flores, L. Alfaro, J. Herrera, Proposal Model for E-Learning Based on Case Based Reasoning and Reinforcement Learning, IEEE World Conference on Engineering Education (EDUNINE), Lima, Peru, 2019, pp. 1–6, https://doi.org/10.1109/EDUNINE.2019.8875800, 2019.

[40] S.K. Gill, G. Kaur, G. Shankar, Veeramanickam, Solving the element detecting problem in graphs via quantum walk search algorithm (QWSA), in: N. Marriwala, C. Tripathi, S. Jain, D. Kumar (Eds.), Mobile Radio Communications and 5G Networks, Lecture Notes in Networks and Systems, vol. 588, Springer, Singapore, 2023, https://doi.org/10.1007/978-981-19-7982-8_36.