DESIGN AND DEVELOPMENT OF E-LEARNING SYSTEM USING INTELLIGENT TECHNIQUES

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ABSTRACT
It was created here, an adaptable and intelligent web-based e-learning system. Techniques for more effective e-Learning systems have made substantial progress over the past few years. We describe the main components of an adaptive learning intelligence algorithm meant to fulfill the teacher's objectives and to create a close relationship with the learner, monitoring and adapting the teaching based on a wide variety of evaluations of their knowledge and performance. Future study in this area has the potential to have a substantial impact on education. Educational institutions will benefit from better learning systems developed in collaboration with trainers, teachers, and subject matter experts.

KEYWORDS: Intelligent Techniques,e-Learning,information technology,Development

INTRODUCTION
Today, e-Learning is defined as the use of information technology to facilitate and support learning in the classroom. E-learning can help any business, whether it's a school or another form of establishment, by allowing it to increase its capabilities. For example, an e-learning system can provide access to educational resources 24 hours a day, eliminating the need for expensive group training or at least reducing their duration and increasing effectiveness. Technology has altered the paradigm of education when it comes to using e-learning systems. Corporate trainers are still needed, despite the rise of online learning. Teachers are responsible for overseeing and evaluating the design of online training materials, providing assistance to students, keeping an eye on their progress, and making improvements to the materials depending on feedback from students, performance, and other factors. In addition, in many training circumstances, human interaction is priceless. The consultant's or trainer's role will be enhanced by software agents that can perform additional tasks to assist students, thanks to emerging technologies that incorporate artificial intelligence. As a training aid, e-learning will let staff train more students, faster, and more thoroughly.

LITERATURE REVIEW
SUN DUO, ZHOU CAI YING (2021) Traditional e-Learning systems have a serious problem with personalization. Personal characters in e-Learning are the focus of this study. An intelligent agent-based system for personalizing e-learning has been designed and implemented in the study. The paper introduced the system's structure, workflow, intelligent agent design, and intelligent agent implementation. We discovered that the system could help students take more responsibility for their own learning, allowing them to receive a more personalized knowledge service. Consequently, we came to the conclusion that it might be possible to implement self-learning and self-promotion in the age of lifelong education.

IRAKLIS KATSARIS (2021) Technology and the use of modern equipment have allowed for significant advancements in the field of education. The old adage of "one size fits all" is starting to lose its luster these days. As part of the study, researchers are looking at ways to tailor learning environments to individual students' needs. Learning Styles are commonly used in adaptable platforms to improve the learning experience. Based on a review of 42 publications published between 2015 and 2020, we examine the learner model, adaptability module, and domain module. It is imperative that e-learning systems contain new adaption mechanisms that are compatible with educational ideas. Adaptive E-learning Systems and Learning Styles are the focus of this paper, which seeks to provide an overview of their theoretical and technological foundations. This survey of the literature is intended for those working in this subject as well as those who will be designing and developing adaptive platforms in the future.

TUMAINIKABUDIILIASPAPPASDAG HÅKONOLSEN (2021) Massive advances in artificial intelligence (AI), mobile internet, and cloud computing have all had a profound impact on the way students are educated. Advanced AI-enabled learning systems have emerged in recent years and are gaining popularity due to their capacity to offer educational information and adapt to the particular needs of students. These systems are becoming more and more prevalent. In spite of the fact that these new educational platforms satisfy students' demands, only a small number of them have been put into practice in order to solve the concerns and issues that many students confront. Our study's systematic mapping of the AI-enabled adaptive learning systems literature was done from this perspective. Over the course of 2014 to 2020, 147 research studies were analyzed. AI-enabled learning interventions have been identified, authors associated with major research themes in AI-enabled learning systems have been visualized, and common analytical methods and related techniques used in such learning systems have been reviewed, among other things. This paper's major contributions include these findings. Use this mapping as a reference for future research on how to create AI-enabled educational systems to solve specific educational problems and enhance the learning experiences of students and teachers alike."

XIAORAN FU, K. LOKESH KRISHNA AND R. SABITHA (2021) Teachers and students should expect better educational experiences thanks to AI-aided educational institutions' significant use of an e-learning environment. Higher education in China is heavily influenced by e-learning or online learning. There is a challenge in China's higher education to utilize e-learning to improve course resources, student learning type prediction, teaching quality, and customer service. Because of this, a framework based on artificial intelligence (AI-EELF) has been presented in this research to help China's higher education overcome obstacles associated with deploying e-learning modules. An adaptive learning environment makes effective use of the data collected by students. Using the AI-EELF technique, a variety of learning models are introduced to help teachers be more effective and better predicts how their students will learn. Research shows that the AI-EELF can accurately predict students' learning styles and increase the quality of their education compared to other techniques.

S. BHASKARAN & RAJA MARAPPAN (2021) Data mining relies heavily on decision-making systems. The subject of data mining has evolved into one in which the interactions, decision-making processes, and overall experience of users must be utilized. In contrast to the traditional head-to-head approach of educating with culture, e-learning is now a progressive way to deliver long-term online education. The number of people benefiting from various programmers is growing steadily thanks to the growth of e-learning. In spite of this, the wide range of pupils on the internet brings additional challenges to the conservative one estimate fits all learning systems, which provide a single set of learning resources to all learners. It takes longer to process queries and provides less accuracy in the final recommendation for well-known recommender systems that have these issues. A new transductive support vector machine-based hybrid personalized hybrid recommender for machine learning public data sets is the primary goal of this project. It is via the habits of the students that the learning experience has been attained. Some of the novel tactics that are being tested to increase the performance of a hybrid recommender are outlined in this research. The learner dataset will be preprocessed using a modified one-source denoising technique. Performance measures will be improved by modifying the anarchic society optimization technique. For mining the sequential pattern of learners, an improved and generalized technique based on sequential pattern analysis is proposed. These habits and interests will be evaluated using an improved transductive support vector machine. Learners' confidentiality rates are being analyzed by these new tactics, which then make recommendations based on the results of the analysis. In order to test the suggested generalized model, it is used to mimic public datasets for machine learning such as movie and music data as well as food and commerce data. The results of the experiment show that the enhanced clustering approach discovers clusters of random size. In terms of projected absolute error, accuracy, ranking score, recall, and precision metrics, the recommended recommendation strategies outperform the current methods by a wide margin. The proposed datasets have an accuracy range of 82% to 98%. A range of 5 to 19.2 percent is seen in the MAE statistic for public datasets that have been simulated. Experimentation has shown that the recommended algorithm has a lot to offer in terms of quality and performance.

METHODOLOGY

INTELLIGENT ALGORITHM

The study makes use of rule-based association mining and group-based filtering. Two phases make to an intelligent algorithm:

Step1: Using a rule-based system to find relevant training resources for users in a variety of areas.

Step2: Making use of a group-based filtering algorithm to direct users to relevant teaching resources. The algorithm for association rules mining consists of three phases:

Step1: The process of frequently producing item sets As long as the item-appearance set's frequency falls below min sup; it's considered a frequent item-set in this context.

Step2: All non-spatial subsets are generated for each common item set l.

Step3:if a non-spatial subset of the frequent item-set l is considered, then

$$\frac{\sup port\_count(l)}{\sup port\_count(s)} \geq \min\_conf$$

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Once that is done, the s=>(l-s) rule is created. A transaction's support count(l) and support count(s) denote the number of transactions that contain item sets l and s, respectively, with min conf representing the minimal confidence thresholds.

It is possible to categories teaching resources into various subcategories. Then this information is then used to develop associations through the use of an algorithm known as a "association mining algorithm. The category of educational resources is located on the rules' left side. In addition, the regulations are categorized and chosen. The category for proposing educational materials should be provided by the useful guidelines. S1-Sn is an example of an association rule recommendation that yields a set of N categories. Recommendation categories are represented by S = S1, S2, S3, Sn Category Sn's instructional resources may be found in N(Sn).

DATA ANALYSIS

Listed below is a diagram of the collaborative filtering algorithm

Step1: Representation. A user-item evaluating matrix (mn) is one possible interpretation of the alleged input data. R. m is the total number of users, and n is the total number of items. Appraisal value is linked to the content because Ri,j is the value that a user assigns to a jth item. The appraisal value shows whether or not the item is a teaching resource in an E-learning environment. If the user selects resources, the number 1 indicates that the user has done so, whereas zero indicates that the user has not selected resources.

Step2: It's time to look for a nearby neighboring set A neighbor set N1,N2,N3,Ns is formed and organized according to the degree of similarity between a user U and its neighbors. Even if U doesn't fall into one of the 'N1, N2, N3, Ns' categories, it is nevertheless sorted according to SIM (U, Ns).

Step3: Developing a suggestion. Thereafter, interest levels for items and their top-N neighbors are computed. Assuming user a and option set Ia, we may apply formula 2 to determine the degree of interest in item j.

$$p_{a,j} = r_a + \frac{\sum_{u=1}^{n} w_{a,u}\left(r_{u,j} - r_u\right)}{\sum_{u=1}^{n}\left|w_{a,u}\right|}$$

Among them are: Rarely represents the average value that a user assigns to a given object, and U is the collection of items that are closest to it. WjI's user-to-user similarity, Item j's evaluation value is given by the user u. The average appraised worth of an item as determined by a user u is represented by Ru. For each item, the user i's interest level is calculated individually. We use N items as a suggestion set since they have a higher interest degree than the item itself but do not belong to it. Top-N.

The collaborative recommendation is used after the association rules are used to identify the categories of interest. We employ the collaborative recommendation in N for eachSnS. (Sn). Supposedly, teaching resources for eachSn,Q should be considered. If you're looking for a set of recommendations, you'll find them here: Each commodity's interest rate is P(It1), P(It2), P(It3), P simultaneously (Itq).

Using this approach, we propose the following resources. The category weighting approach is used to recommend products because the user has varying levels of interest in each category. It's the user's interest weight for each category n S based on P(It,j) (t=1,2,3,...,t j=1,2,3,...q) Confidence is used to determine interest weight. Association rules are used to determine a person's level of confidence.

$$F_{t,j} = w(S_n)p(I_{t,j})$$

The size of Ft,,j（t=1,2…t, j=1,2…q） is taken as the recommendation.

This section provides an overview of the general architecture of an intelligent algorithm. Algorithm is an adaptable and intelligent e-learning environment where content is given with expert system support and is personalized based on VAK learning style. Students and teachers must sign up and connect in to the system in order to use the clever algorithm in a classroom setting. As a result, both teachers and students must first sign up for the system. There are links on the main page for teachers and students to sign up for the course. The administrator of the system verifies teacher registrations. Once their registration has been verified, teachers can access the system with their assigned usernames and passwords. Students who want to enroll in this programmed must first pick the schools and teachers they would like to work with. Students' registration information is automatically shown on the teacher's page when they submit it correctly. In order to verify, arrange, or delete a student's registration, each teacher has access to their own class's learner list. Students who haven't had their registrations confirmed by the teacher yet aren't able to log in. These students are notified that their registration is pending the approval of their instructor. In order for a student to take the VAK learning style

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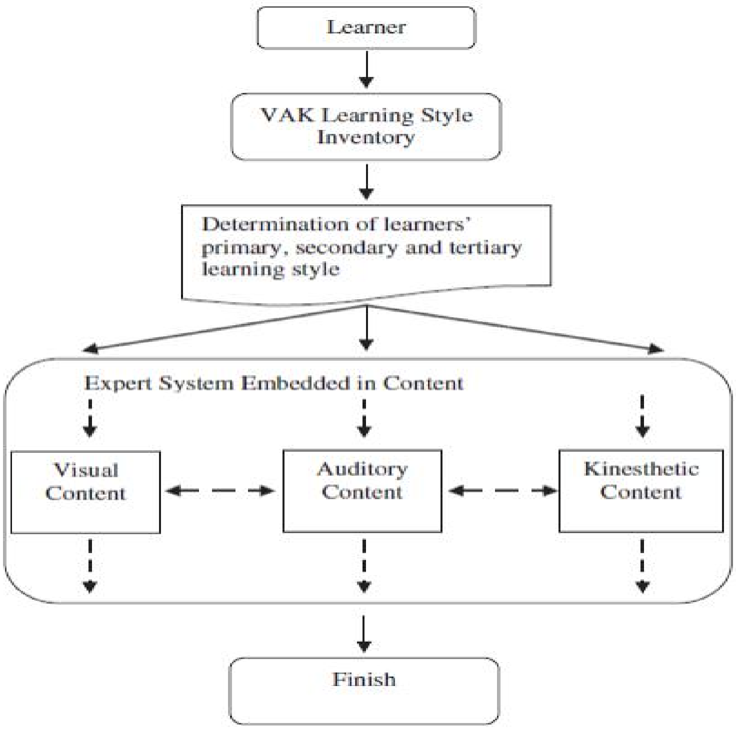
assessment, the teacher must first validate their registration. Gokdag developed the VAK learning style measure that is embedded within the site (2004). The researcher conducted all of the studies on this scale. The learner's primary, secondary, and tertiary learning styles, as determined by the learner's first login to the system and as measured by the scale, are automatically calculated and stored in the system's database. This is a one-time event that determines the learning styles of the students. Learning styles of students who have completed a learning style inventory are immediately routed to the material most appropriate to their styles. As a result of this advice, each student follows a specific order when completing the LOs associated with their preferred learning method. These students are making progress in their primary learning style thanks to an expert system hidden within the text. The system now has complete control over any learner who is developing in their primary learning style. With the help of experts, any learner who is taking the content of primary learning style receives the essential suggestions and solution supports that are relevant to their main learning style in all LOs in the content. A learner's performance is the only factor that affects the presentation of these hints and intelligent solution assists. For example, students of the same learning type may receive varied recommendations and intelligent solution support depending on their performance. Los was designed using an expert system on an intelligent algorithmic learning site. In LOs, an expert system checks to see if any learners have achieved the "adaptability point."

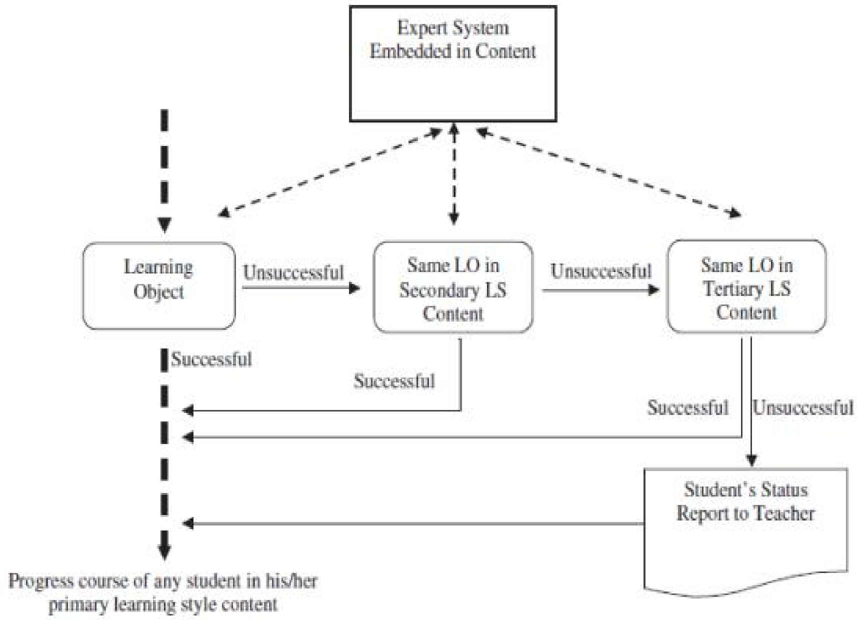
At this stage of adaptability, the expert system makes a judgement on the learner. Learners can choose to be redirected to their primary learning style or their secondary learning type for this decision. When a learner completes a current learning objective, they are guided to the next learning objective in their primary learning style. If a learner fails to complete the current LO and reaches this point, the learner is redirected to the identical LO in the secondary learning style. Secondary-style learners who are given the same lesson plan understand that there are many different approaches to solving difficulties and completing the LO. For those students who have finished their secondary learning objectives, they can proceed to the main learning objectives that follow. The same approach is applied to learning failures in secondary and tertiary styles of learning. A student who completes a LO in this manner is returned to the previous LO in their primary learning style and is given the opportunity to complete the remainder of the course. The teacher receives a report about a student who is failing in a tertiary learning method as well. When a student's case is brought to the attention of the teacher, the primary learning style is resumed for that student. As a result, students may be able to access various content based on their performance on this site. Below is a diagram of the browsing and adaptability architecture,



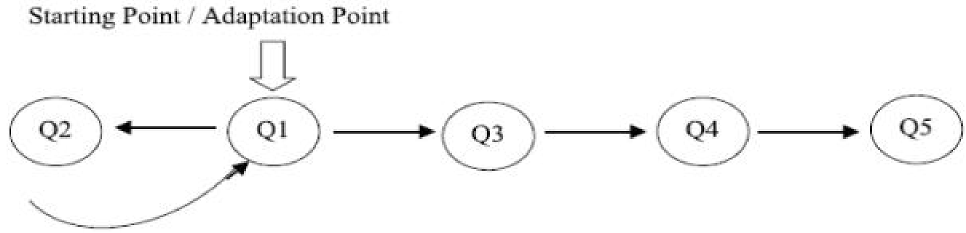
E-learning system content based on an intelligent algorithm was selected at random and two LOs were presented as examples. The sample LO that was chosen for this article is described in detail below.

LO_6: One of the LOs designed for permutation subject

LO_45: One of the LOs designed for probability subject



Schematic view of browsing support between contents of primary/secondary/tertiary learningstyles



Scenario prepared for Activity_6 and presentation plan of questions within the activity

This is a permutation-related learning object. The scenario for LO 6 and the content of LO are depicted in the figure on the right above. This LO's content is divided into five separate questions. The first question in the LO is answered by the learner. An answer of "yes" indicates that the learner is ready for Question 3. The learner who properly answers the third question is then directed to the following question using the same logic. Learning Objectives (LO) can be completed by properly answering the third, fourth, and fifth questions of the test. Intelligent solution supports will be provided to students who are unable to answer the third, fourth, and fifth questions correctly. Depending on the student's response to the second question, he or she will receive assistance and advice on how to solve the problem. The second question's tips and solution support shows the learner how to tackle the difficulty. The student who successfully answers this question is returned to the first question. The LO's "adaptability point" was the first question that was asked. At this point, the student must return to the initial question and re-answer it. If the student answers the question properly this time, the "„adaptivity point" determines whether or not the LO was successfully completed. There, the learner is tasked with answering LO-related questions. Learner's inability to answer the first question correctly is determined by the "adaptivity point" if it occurs again. Consequently, the student will be directed.

CONCLUSION

The paper proposes a new intelligent algorithm based on association rule mining and collaborative filtering. Personalized e-learning is another area where the algorithm is being used. Data shows that algorithm can provide greater support for online learning.

Architecture of intelligent algorithm based e-learning system.

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