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REVIEW

Responsive e-learning dynamic assessment structure using intelligent learning design

Estructura de evaluación dinámica de e-learning con diseño de aprendizaje inteligente

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ABSTRACT

A previously created e-learning model and learning system research have been conducted based on the 'one size fits all' idea. This approach ignores the distinctions between learners and pupils, delivering the same educational content to each one. With the advent of a new R&D style, researchers' and students' demands and preferences will shift. These days, quick e-learning courses come with online videos, audios, and desktop recording capabilities that used to need separate software. In contrast to printed textual lectures, students learn more effectively and enhance their abilities using onscreen instructional materials. As a consequence, there is a need for more adaptable learning and knowledge-based e-learning model assessment. This article focusses mostly on the learner modelling module and illustrates an adaptable model for an e-learning system. Students who are modelling are accountable for meeting these criteria in order to assess the degree of performance of learners in an online learning environment and satisfy specific needs.

Keywords: Student Model; Assessment; Intelligent E-Learning; Adaptive Learning; Learning Target.

RESUMEN

En el pasado, el modelo de aprendizaje electrónico y la investigación sobre sistemas de aprendizaje se han basado en la idea de «talla única». Este planteamiento ignora las distinciones entre alumnos y estudiantes, ofreciendo el mismo contenido educativo a cada uno de ellos. Con la llegada de un nuevo estilo de I+D, las demandas y preferencias de investigadores y alumnos cambiarán. Hoy en día, los cursos rápidos de e-learning vienen con vídeos en línea, audios y funciones de grabación de escritorio que antes necesitaban un software aparte. A diferencia de las clases de texto impreso, los estudiantes aprenden más eficazmente y mejoran sus habilidades utilizando materiales didácticos en pantalla. En consecuencia, es necesario un aprendizaje más adaptable y una evaluación del modelo de aprendizaje electrónico basada en el conocimiento. Este artículo se centra principalmente en el módulo de modelado del alumno e ilustra un modelo adaptable para un sistema de e-learning. Los alumnos que modelan son responsables de cumplir estos criterios para evaluar el grado de rendimiento de los alumnos en un entorno de aprendizaje en línea y satisfacer necesidades específicas.

Palabras clave: Modelo de Alumno; Evaluación; E-Learning Inteligente; Aprendizaje Adaptativo; Objetivo de Aprendizaje.

INTRODUCTION

Teacher-learner models that compute in an intelligent and adaptable way make up the expertise learning framework. A system based on fuzzy logic is utilised in artificial intelligence communities to accept or modify teaching-learning procedures to match the demands of individual learners. The expert and intelligent learning model utilised or accessed via the Web server is the Student Learning Model in the Adaptive Intelligent E-Learning and Evaluation Environment. Millions of students worldwide may access and benefit from the original adaptive intelligent Learning and Evaluation Environment at no cost thanks to web-enabled computer systems. The adaptive student model is assisting most students in quickly and successfully meeting their learning goals and needs by providing them with personalised, flexible online learning opportunities unique features of each user's learning.(1,2,3) It is crucial to remember that enhancing e-learning or learning performance depends in large part on the students' preferred methods of learning.

Additionally, evaluating how well students' learning styles are adjusted has a significant impact on their success. The student model is based on an analysis of a web log in the building of an adaptive intelligent e-learning framework based on fuzzy-clustering technique.(4,5) This approach extracts important phrases from sites viewed by learners. Both the statistical k-means clustering technique and the fuzzy-clustering methodology are used to forecast students' interest in receiving learning information from the semantic web. Six out of the ten adaptive e-learning hypermedia systems that were investigated by Brown et al. did not seem to have published any quantitative evaluations. These systems explicitly leverage learning styles as their adaptation mechanisms. Fuzzy logic and web-based current methodologies are inherited by the intelligent adaptive student learning and assessment framework, giving it its own features.

- The foundation for clever adaptable students is not reliant on the classroom. The framework is applicable not just in a classroom setting but also in every location in the globe at any time.
- The cross-platform delivery of the intelligent adaptive student framework is predicated on adaptive knowledge. Most of the platform may benefit from other online resources that provide instructional content for use in educational systems. Individual adaptation is provided by the intelligent adaptive student framework. A flexible learning environment has been built up based on each student's knowledge, information, and needs as well as their comprehension of the subject matter and teaching style.
- The intelligent adaptive student framework has been given with adaptive hypermedia systems.
- The intelligent adaptive student learning and assessment framework has centralised maintenance.
- Web-based hypermedia and multimedia methods were used to develop and organise learning materials and course content on a dynamic basis. The only globally distributed study materials and servers that are maintained on-site.

Why using the intelligent adaptive student learning framework is economical?

Once the course materials or content are created, many students and learners reuse them. The significance of clever adaption according to knowledge level. The capacity of an adaptive learning system to adjust to a particular learner or student during the teaching and learning process is often cited as evidence of the system's intelligence. Adaptability is a key feature of web/online learning as opposed to other standalone learning systems and one-size-fits-all approaches. These are:

- The adaptive e-learning system will be beneficial to a much larger spectrum of learners. The system, namely the learner's design, is often unsuitable for other students because to the wide range of knowledge, objectives, backgrounds, learning styles, behaviours, preferences, and educational backgrounds among the learners.
- The amount of information that each student has is rapidly increasing. When the content pages and learning materials become banal and boring to a single student, they will become more simpler and less intriguing. Initially, the pages and learning materials are quite challenging and complex for an individual learner. The degree of knowledge and presentation standards of students must alter as they study.
- Most of the time, this method may be used by students across the globe who lack access to instructors or classrooms for in-person learning support. The system ought to function similarly to a classroom counsellor, offering instruction and supporting specific students.

The remainder of the study, in part 2, discussed pertinent issues and current research while outlining the framework for student adaptable intelligent learning and assessment. Many learner models were then followed by a description of the suggested model and the specifics of its implementation. Section 3 concludes by summarising the work that has to be done in this area and defining its scope.

Knowledge based adaptive intelligent learning and assessment

The importance of the student model in the Adaptive Knowledge Based Learning and Assessment System is that, in most of the three phases of the adaptive process, details of the learner, process the information and quiz/test was initialized and updated, and modified using the student model in order to adapt the information.

In the adaptive system, student models are of greatest importance and very essential. The adaptation of the system is primarily a choice and presentation of each successive learning activity as an entire process involving all students' knowledge of the subject in which they have learned, together with other appropriate factor of learners kept within learner/student framework. In view of individual learner's needs to update and adapt the interaction with the system using a student model.

One important point to bear our brain is real power of learning methodology does not come from repeat something which accomplished elsewhere, but by using it to do what would have been impossible without it.[6,7] Today's examples of eLearning on the net, largely a small amount of hyperlinks connected with the uploading of lecture notes and notes in HTML format. The previous observation, the power of eLearning lies in taking advantage of a broad range of capabilities that technologies are able to provided. Mostly, they provide teaching materials and assessments adapt the needs of their students or learners. This should include a web application for real time. Another efficient technology offers multimedia presentation, the possibility of additional emerging skills, rapid simulations and hypermedia display.

Adaptive intelligent learning is the main goal of delivering correct and appropriate content to learners when they need it, at the right time in a way that suits their needs.[7] We're focusing on what we need to do in order to achieve this ambiguous goal within the eLearning context and synthesizing it. If the knowledge base is spread between different servers and used appropriately algorithms for teaching-learning through Remote login, this process shall be carried out. E-learning system Figure1 shows the following basic component or module of a Knowledge Base adaptive System, which is to be introduced in brief:

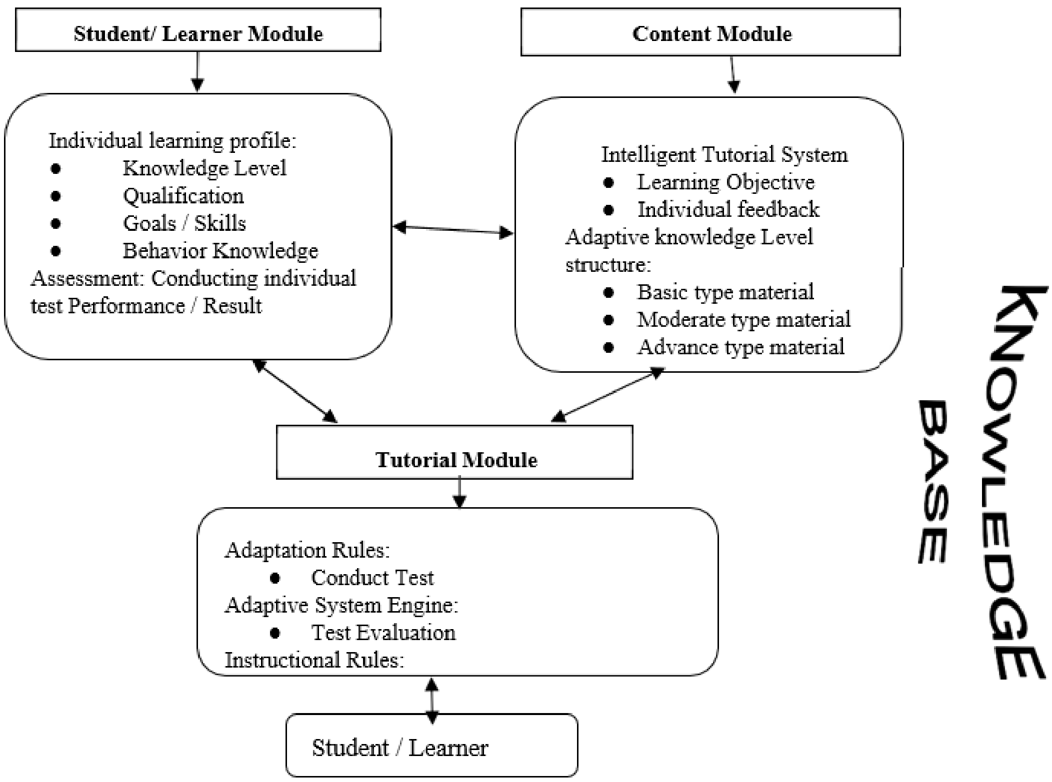

Figure 1. A Framework for a Learning Management System consisting of two types of evaluations

Content model: Knowledge and skills is the domain of a content model, which is their relative construction or interconnection. This is expertise module of what is to be learnt and how to evaluated, which is capture and describe the contents of the course, experiments, illustrations, along with direction for tutors how to construct content of course material, experiment and illustrations for the framework. The model connected a hierarchical set of knowledge and skills on the basis for assessments, diagnosis, guidance and corrective actions.

Learner`s/student mode: An individual's experience profile and quiz will be included in the model of a learner or student, which may also have other characteristics, to capture and analyze the essential aspects of pupils for their own learning purposes. The measures for assessing the position of learners on these aspects shall be included in this context.

Instructional model: This model manage and check the content quality, tutorial presentation and find out mastery of learner`s by observing learner`s model co-related to model of content, managing inconsistencies in a conceptual approach and for individual learner prescribed optimal learning path. The information contained in this model provides a basis for deciding on how content is presented to the individual learner, when and where intervention should take place.

Adaptive system: In order to demonstrate an adaptive learning model, the adaptive system shall integrate and use information obtained from previous models.

Content model

The content models are divided into two categories: the need for an delivery system, as well as the necessity of course material and contents of leaning to be delivered. We require the framework which is automated, durable, versatile as well as sustainable to the delivery side equation. Content automated means that any content that has been designed in accordance with the content requirements will be served by the system. Durability means you're living in the Internet and should be able to provide instruction for more than one user simultaneously. Versatile means flexibility or adaptability, which requires various levels and order of content to be used. Sustainable refers to a system that is able to cope with increased demands, e.g. the provision of more components, maximum users or so on. The subject topics shall be prepared so a delivery system should be adapted to the requirement of specific students or learners, within the context of learning material and course contents. The delivery system should be prepared predictable parts for the each content and course material aggregation, so it can anticipate what is going to happen. Which means it is necessary to build on a common specification for course material and all the contents provided by this system. Depending on the content and purposes of the course material, the issues relating to this system such as grain size will be different.

Student Learning Objective and Outcomes: In particular, the requirement that content be able to develop a similar specification with current industry R&D associate of student learning objective and outcomes such as IEEE LTSC 2003,[8] IMS Global Learning Consortium 2001.[9] Student learning and Objective and Outcomes (SLOOs) are power-point presentations, small functional factors, tutorials, activities, practical examples, questions-answers, case-studies simulations and assessments. But they are used for creating larger collections of teaching materials, instead of building a castle. In order to meet individual requirements for training and performance support, SLOOs may be used separately or in combination with computer software, educational consultants or the learners themselves.

In the modern scenario, SLOOs are assembled in advance of their delivery. During this meeting, the arrangements are made for the implementation of these earning objectives to achieve the educational objectives. These collections will be specified using the Advanced Distributed Learning 2001[10] specification for defining courses. The basic idea is to divide SOLOs collections in a way that it contains sub-collections, each containing all the educational components necessary to teach this skill. The Adaptive System may use the hierarchy to determine what is needed for learning and how it should be learned.

Different level of knowledge frameworks: The establishment of different level of knowledge framework in the content model for each e-Learning system crucial to establish a dependency relationship. It provides the basis for the assessment status of a given topic or SLOOs, the cognitive assessment causes the problem, if any, the instruction or correction of what SLOOs need to teach in order to solve the problem area or to present a new topic. Different levels of expertise, abilities or skills may be assigned to each element or node in the framework of expertise level. We include some level of knowledge examples are:

- Fundamentals Level of Knowledge (FLK) content: It covers meanings, explanation, exercises, examples, flowcharts, expressions, formulas, and symbols so on, what part of the content they cover.
- Moderate Level of knowledge (MLK) content: It describes systematically one after information's, relations between function, sub-functions and so on how part of the contents is covered.
- Advance Level of Knowledge (ALK) content: It contains the correlation between different topics/concepts and the definite relationship among FLK and MLK nodes, depicts each and every into a huge image and addresses the why part of content to be covered.

To restrict the level of knowledge framework every node interrelated of SLOOs to one level of knowledge helps to ensure the course material break up to relevant brain size, by limited scope what would be in any single node. This limitation also indicates that distinct approaches are required for creation of instructions and evaluation. There are a number of different kinds of knowledge which require different approaches. In order to enhance the level of knowledge, we propose a further set of guidelines:

- The FLK course will introduce straightforward latest ideas, annotations, definitions and formulas in educational approach although the evaluation of their potential to recognize basic definition, understand several procedures, rules, etc. would be based on an evaluation of competence with regard to these concepts.
- The MLK will be taught in an experiential environment where the learner/students enhanced their skill or procedure, solve problems, whereas the evaluation concern the ability of learner's that actually

perform a procedure or apply a rules, not just recognize it.

Finally, ALK instruction is carried out after the learner has been provided with appropriate basic information (FLK–MLK), then the large image might be explored, may be case studies or well- designed analogies and so forth, although evaluation comprise student being able to transfer FLK-MLK to novel areas, explain a system or phenomenon, predict outcome. Each of these outcome types is represented by the results tests described previously in relation to an electrically teacher study.

A collection of Student Learning Objectives and Outcomes (SLOOs), which teach or evaluate any component of a concept or skill, is linked to every node. The simplified hierarchy of elements (nodes) or framework and correlated level of knowledge is shown in figure 2.

As a general rule, we define various types of knowledge associated with their specific teaching and evaluation methods. Now the question is: How can we optimize assessment and diagnosis of different types of outcomes, and what will happen when diagnosed? Prior to response the above- mentioned queries, we present the student framework concern the repository information of learner‘s current status in relation to the various SLOOs (i.e., domain-related proficiencies).

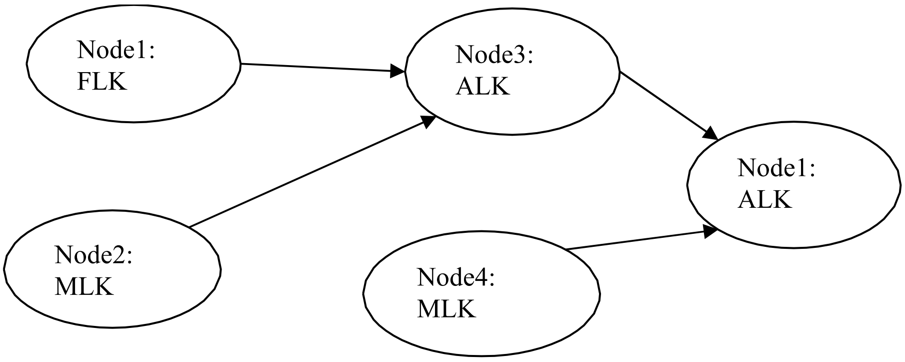

Figure 2. Different level of knowledge frameworks hierarchy

Student model

Information derived from assessment is referred to in the student module, which ensures that proficiencies are identified. The system uses that information to make a decision on the next step.

This decision was about customizing and optimizing the learning experience in the basis of adaptive intelligent e-learning. The evaluation is valid and reliable, nevertheless, a crucial element. One idea is to use known as the Evidence Centre Design Approach for evaluation (e.g. Mislevy, Steinberg & Almond 1999),[11] allows an instructional designer or whomever to: i). Determine the states to be built in respect of learner`s, i.e. abilities, skill, expertise level of knowledge and more characteristics which could be evaluate. ii). Define What is the relevant evidence of a claim, i.e. learner`s performance data, to be admissible, which demonstrate different levels of ability? iii). Determine the evaluation tasks to be carried out in order to obtain this evidence.

Assessing the learner: It concern the question of what is to be evaluated in this regard. There have different kind of adaptation effect for the learner`s: i) Independent domain information: Includes data on learner`s profiles, e.g. cognitive abilities or personality characteristics and allows the system to select optimal SLOOs sequences and formats for their use. (ii) Dependent domain information: it describes knowledge level evaluation via pre-quiz and data of performance to allow the system to initialize a learner model in related to course content, material and SLOOs, remove those already known, and focus instruction or evaluation or both on weak areas.

The assessment of an individual student's characteristics indicates which content and course materials are to be provided in relation to a given set of topics or according to the provision of adequate, alternate formats and media. These steps are part of a valid sequence for the development of educational systems in various fields: i) giving the introductory course material to learner. (ii) Make sure the presentation rules or concepts are followed. (iii) Illustrative examples and questions should be provided. (iv) Provide opportunities for liberal practice as well as case studies. (v) To sum up and call for a reflection.

Therefore, one general rule of sequencing may provide simple subject topics than more complicated ones in these areas, and common rules to deliver certain learning objectives may be applicable in these areas: Introduction, concepts or rules, with examples, interactive explorations, practice and direct evaluation of skills or knowledge, reflection and summarized.

Figure 1 shows the combination of the parts that were modified from Quinn.[12] The typical way in which content is served based on the assumption of a knowledge gap among learners, appears at the bottom of

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this figure. This is due to distinguish between student level of knowledge and structure of the expert level of knowledge that is represented in the contents model. Rules of instruction determine the type of knowledge or skill element that needs to selected next i.e., selecting from a list of un-mastered objects In the upper right-hand corner, a further assessment is presented as another way of adapting instruction to learners' cognitive abilities, educational style, personality or any other factors that may be important. It gives information on how to present the chosen knowledge and skills.

Instructional model

Instructional design may be guided by many general and particular rules for systematic techniques, as those Robert Gagne describes. How will we proceed forward from the guidelines to the SLOO selection process, and why? We have outlined principles from Gagne's 1965[13] book "Conditions for Learning" and will examine the student model approach, which employs minimal instructional methodologies inside the context of an IT system, in order to address this subject. These practices create learning environments, which in turn helps to organize teaching.

Moreover, the media should be chosen appropriately.[14,15] We have included them here because they provide precise principles for creating high-quality e-learning environments:

1. Capture the student's interest (acceptance).
2. Discuss expectations and objectives with the students.
3. Recall or stimulate knowledge from the past (retrieval).
4. Give students a selectively perceived instructional stimulus.
5. Teach students how to employ semantic encoding;
6. Require suitable performance (responding).
7. To offer and reiterate comments.
8. Evaluate the student's performance.
9. Promote transmission and retention (generalization).

One effective method for promoting successful learning and skill acquisition via eLearning programs is to use Gagne's nine-step approach. On the other hand, an e-learning program offers limitless access to papers hosted on the Web, which can never be a replacement for preparing lessons. These kinds of apps won't handle information as effectively, even if they could be useful as amusement or references. In addition to the aforementioned considerations, there are other important tenets and concepts that should be kept in mind while designing an eLearning system. In general, knowledge is action; it is preferable to have various representations of ideas and rules than just one. Therefore, knowledge should be realistic and complicated when it comes to problem-solving activities so that students may show their proficiency via abstractions and reflection. Its attributes cover a wide spectrum of what makes it a suitable adaptation system feature:

i. Activities involving the creation and manipulation of representations would be assigned to the pupils. If the expectation is that the student will have a mental model that matches the representation, then the student has to actively engage in the production or modification of the representations.

ii. The course material and the content should present a concept or guideline in diverse ways. This enables an adaptive engine to provide the learner a single representation that most closely fits their aptitude profile while also giving them extra representations to help them recognise and comprehend this topic for the first time. This multiple representation should include diverse visual representations of the same notion, such as textual and graphic or different graphical representations of same concept and different conceptual explanation methods.

iii. Lastly, students should be given a learning exercise that promotes the integration and reflection of newly learnt information into the body of knowledge. Finally, the system has to provide enough help and support so that students may devote their time to studying content rather than operating systems. This is done to make sure that the student's cognitive energy is focused on understanding the content that will be provided, not on understanding the platform that will deliver it.

From these broad and detailed standards, how would we decide which learning objects—and why—would be chosen? The fundamental method of student modeling is based on a learning system design in which components of low-level knowledge and skills are recognized and divided into the three primary outcomes—FLK, MLK, and ALK—that have previously been discussed. The online representations of the knowledge and skill components, or SLOOs, will be used to assess and educate students through the course. If Further training, assessment, and correction for that knowledge will be considered components that show values that fall short of the minimum mastery requirement. Remedial action will be started if the learner cannot demonstrate mastery during the assessment, which comes after or is integrated immediately into the learning process.

It entails evaluating students' comprehension and application of the system, emphasizing their propensity

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for lifetime learning behaviors, including impulsivity, working memory capacity, and aptitude for inductive reasoning. A further method for student modeling[16,17] uses Bayesian inference networks (BINs) to provide estimates of learner competency about the material.

The SMART and BIN techniques aim to address the following queries: a. To what extent is this subject now mastered? b). If any, what factors lead to learners' difficulties? Typical techniques for assessing success, such as passing or failing or correctly answering two consecutive tasks, do not provide the degree of precision necessary for assessment into cognitive recognition. Regardless of crop size, SMART and BINs provide knowledge of probabilistic values for nodes or subjects. When the adaptive engine decides what to provide regarding teaching choices, it is informed by creating knowledge and an indicator of how successfully a learning target is satisfied.

System engine for adaption

Understanding the fundamentals of the adaptive system engine about content, learner, and teaching models is relatively simple. Choosing the node (element or subject) that will be taught is the first stage; this is determined by a student's evaluation of his knowledge requirements. The next stage is to identify which Learning Areas are offered in this node and arrange them in a logical order based on the unique requirements and traits of the learners. The presentation of the learning objectives will resume when the learner expertise subjects and topic selection procedures are repeated until all topics are expert. This is just a summary; the actual procedure is more involved. The content of the node or subject should be presented independently of each other, and every stage of the node selection process should be scrutinized.

In our approach, selecting a subject is quite accessible since the Adaptive System Engine selects any nodes or topics that still need to be addressed and whose requirements have been successfully met. Other features of our structure include creating a test before takeoff and an evaluation that could use a sequence algorithm. Only one of the Learning Objects' nodes is restricted to a specific function per the authors' requirements; all nodes have been categorized based on their roles within the learning process. This implies that the system can generate a new collection of nodes that includes an assessment job from your first collection for every collection of nodes. Consequently, a new set of functions is offered as a first test. Students who pass an evaluation without presenting are assumed to have learned the necessary material.

The adaptive engine uses a set of criteria to determine which SLOOs should be shown to students when it displays items related to a particular node or subject. These guidelines will consider the data in a learner model, students' interactions with nodes so far, and the content models of each unique SLOO that is part of a single node. Based on the data, the rules determine which LO inside a node has precedence. As soon as each LO is computed, the student receives the most significant priority, meaning the assignment is sent instantly.

An example of how a student's educational object operates. We have investigated how each SLOO in a node is initially given an arbitrary weighted assignment. If students' interactions with nodes are partially filled, one guideline is to lower the importance of all SLOOs and save those that thoroughly perform the teaching function.

For example, a student joining the node lowers its priority. According to the default sequence, these criteria guarantee that the type SLOO will be introduced at the start of the instruction sequence.

However, learners who need a more flexible contextualized learning environment—for example, very specialized and exploratory learners—should also be considered. In order to address this, there is a rule that states that the priority of related assessment-task SLOOs should be increased if the learner is very concrete and experienced and if their contact with the issue is empty. The second rule is meaningless if the student lacks actual and experienced knowledge. On the other hand, if the student disregards the first rule and follows the second, the instructional sequence will start with an evaluation assignment.

The remaining regulations will look at a series of circumstances related to the lesson plans and make similar adjustments to the order of the relevant Learning Objectives. Thanks to all of these guidelines, every step of the student's interaction with the node is meant to be accompanied by an appropriate learning object. Dealing with the rule set's correctness is one of the issues; it should be created so that any student, regardless of their qualities, may have a practical and authentic learning experience.

One method to do this is to employ genetic programming methods like[18] to improve a rule set's performance. According to studies, rule-based system designs[19,20,21,22,23,24,25,26,27,28], are created using this methodology. The overall strategy is to consider each set of rules in the algorithm population as a single set; the rule sets may then be produced using the conventional GP procedures. From our perspective, the intriguing aspect of GP is that it converts a design problem—which involves coming up with a set of rules that successfully serves the learner—into a recognition task, which assesses how well a rule set works in treating learners.

A sizable sample of learning data may be utilized to evaluate learners' prospective experience within a predetermined set of guidelines, and we might use this data as the foundation for our GP methods where evaluation functions drive learning. Furthermore, we have a good chance of success and can avoid many of the hazards associated with rule-based systems by combining computer-driven evolution with human-designed

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rules.

Final summary

In order to increase the efficacy, efficiency, and quality of the learning process, there are several reasons to explore adaptive intelligent learning and assessment frameworks in e-learning. The most excellent e-learning solutions in online assessment may be designed, developed, and used for student learning. An evaluation typically consists of crucial learning events and an understanding of the progress that has been accomplished. As nothing more than an online lecture, the present level of e-learning has lecturers creating electronic copies of conventional printed student guides and publications. The framework for adaptive intelligent learning and evaluation enables the dynamic arrangement of pages to present the learner with the appropriate information at the appropriate moment. Concerned about adaptive education based on their adaptive development of emerging content or skill knowledge or material modifications depending on learner styles, cognitive capacities for adaptable decision-making in education. In order to address the needs of individual learners, the time has come to design e-learning systems that can be relied upon to give distinctive, efficient, and exciting training experiences. A customized learning environment offers detailed descriptions of the material parts, learner data, and legitimate logical maps connecting the learner's attributes to the content.

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