Adaptive learning materials based on learners’ degree of knowledge

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ABSTRACT

E-learning has been on the rise for the last couple of years and has quickly become an active area of research. It has the potential to completely change the educational sector; however, it presents a number of issues, such as: not accounting for learning styles and knowledge gaps that learners might have. Researchers have invested a lot of time in searching for a solution to these issues. This literature review aims at discussing these issues and presenting possible solutions to an ontology-based personalised adaptive learning system that is able to identify knowledge gaps in learners and how to generate the appropriate learning materials using systems such as AQGs’.

CCS CONCEPTS

• **Computing methodologies** → Artificial intelligence • **Applied computing** → Education • **Theory of computation** → Formal languages and automa theory

KEYWORDS

E-Learning, Ontology, AQG, Adaptive learning

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1 INTRODUCTION

Electronic learning, otherwise known as e-learning, is described by Oxford as “learning conducted via electronic media, typically on the Internet” [1]. E-learning has become majorly important in the last few years due to the COVID-19 pandemic [2], where all students and educators were forced to work remotely. Students had to learn through online tools with educational applications such as Zoom and Google Meet. However, e-learning has been on the rise since years before the COVID-19 pandemic. E-learning comes and evolves with technology; hence, it has the same objective, to innovatively transform the domain it lives in. In the case of e-learning it is education. E-learning has had a substantial impact on our lives as it makes accessing educational material online easier, making it possible for anyone to learn anytime, anywhere. Furthermore, it allows for a new and easier means of online communication and collaboration. Higher educational institutions make excellent use of e-learning which includes: pre-recorded lectures, online meetings via Microsoft Teams, and assigning tasks such as assignments and readings. However, e-learning comes with a “one size fits all” policy. E-learning provides the same educational materials to all students studying a particular course/topic. Although this static material is necessary for students to get a grasp on core concepts, this approach comes with disadvantages. Firstly, each individual learner is unique when it comes to their learning style, how fast they process information, how well they understand certain topics, what they struggle with the most, and so forth [3]. Learning styles refer to the idea that people differ in terms of which mode of instruction or study is best for them [4]. It is possible to determine a student's strengths and tendencies, as well as behaviours that could present difficulties in academic settings, by looking at their learning style profile [5]. Learning styles are classified into three groups, active and reflective, sensing and intuitive, visual, and verbal [5].
Adaptive e-learning is whereby certain educational materials and resources are selected and presented for a particular learner in an effort to better their understanding of a concept(s) they are struggling with. Adaptive e-learning takes into account each learner's characteristics and generates educational resources accordingly to ensure that any knowledge gaps are filled.

Assessing a learner's knowledge and understanding is important as it allows educators to reflect, measure success, and identify what they can improve on to improve the performance of their students. Assessing a learner's knowledge can be done multiple ways, such as through quizzes, tests, exams, etc., with quizzes being the most effective according to O. Rodriguez Rocha [6]. All these types of assessments require good quality questions about the topic being assessed. There are two types of questions: objective questions and subjective questions. Objective questions are fact based questions. Examples include Multiple Choice questions and True or False questions. Subjective questions are also known as open ended questions as they require your opinion or interpretation. Subjective questions can really test your understanding of the topic as they allow you to argue your case. However, marking subjective questions can be timely and costly. Objective questions, on the other hand, allow you to assess a broad range of knowledge but also require little time marking answers, as they are either correct or

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incorrect. The biggest downside with objective questions is the time it takes to manually generate a good quality question [7].

Automatic Question Generation (AQG) involves automatically constructing quality questions from structured (ontologies) or unstructured (e.g., text) [8]. AQG aims to improve costs of generating high quality questions. AQG's would be particularly useful in the context of setting large exams or tests (e.g., nationwide) as they would be able to generate consistent questions capable of covering all concepts of an educational domain. Furthermore, it would allow educators to spend more time teaching and engaging with students, as they would not have to spend a monumental amount of time setting exams and tests. Therefore, it would be a major educational benefit to have AQG systems in educational institutions.

One method of implementing an AQG system is by using ontologies. Ontologies are knowledge models that are used to create artificial intelligence systems [9]. Ontologies consist of classes and properties that describe a domain of interest. The relationships between the classes and properties in an ontology can be written in formal and machine-processable statements known as axioms [10]. In this literature review, we aim to discuss ways in which ontologies can be used to create adaptive learning materials for learners by generating unique questions for each learner using an AQG. The questions generated are based on a set of results obtained through assessments that indicate where the knowledge gaps of each learner are.
In Section 2, we discuss and conduct a critical analysis of the research and work that have been done thus far for adaptive learning. In Section 3, we discuss which methods have been the most successful and the implications this has. Furthermore, we discuss the possible gaps in the domain of adaptive learning and how we could capitalise on them. In Section 4, we draw our conclusions from this literature review.

2 OVERVIEW OF CURRENT WORK

Susanti, Y. [11] discuss the relationship between an AQG system and an adaptive system called CAT (Computerised Adaptive Testing). The primary function of CAT is to adjust the difficulty of questions for learners to test their true proficiency in a topic. Learners are expected to take an initial standard test to test their base knowledge of the content. Their results are then examined by CAT, and new questions are generated based on how well they performed in the initial test. The better they performed, the more difficult the questions produced by CAT were, and vice versa. Although there is an initial design for CAT, there have been very few attempts to integrate CAT with AQG.

One attempt to integrate CAT and AQG was done by Bejar, I.I. [12]. Bejar, I.I. [12] used item models and supplied items for calibration. Thereafter, the calibrations are used to estimate the ability of the model, which produces a new item based on this. The purpose of the adaptive testing was to assess the psychometric feasibility of on-the-fly testing. It's called on-the-fly-testing since items from the item model are supplied at delivery time.
Using inspiration from CAT and AQG, it is possible to come up with a general model that shows how an AQG could be integrated with an adaptive learning system.

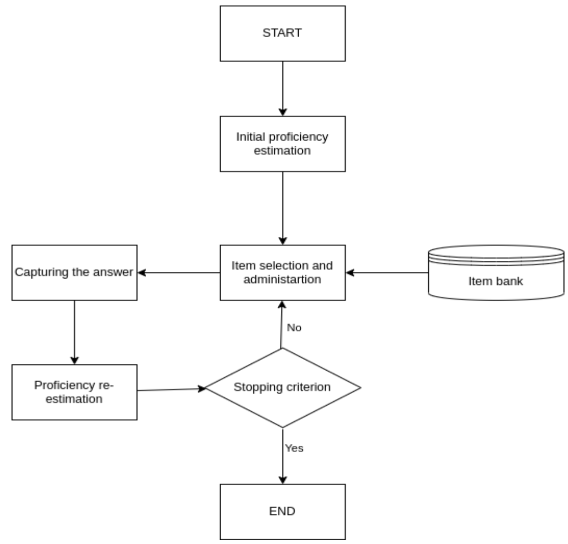

Figure 1: Steps of CAT as per [11]

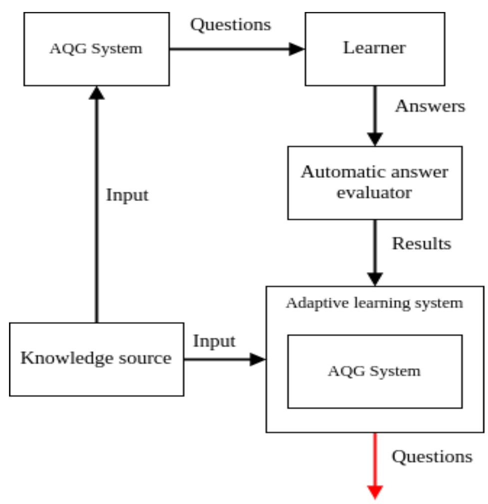

Figure 2: General relationship between AQG and adaptive learning

Figure 2 models the steps of being able to dynamically generate questions using an adaptive learning system. The model consists of five main classes. An AQG system, a leaner class, an automatic answer evaluator, an adaptive learning system, and a knowledge source

1. The AQG is responsible for generation of questions used for assessment
2. The learner class represents a learner object that produces a set of answers based on the questions generated by the AQG.
3. The Automatic answer evaluator uses the answers from the leaner class and assesses the correctness of it. Thereafter, it outputs the results of the set of answers.
4. The adaptive learning system uses a knowledge source and data results as input. It assesses the results with respect to the

knowledge source. This assessment includes identifying any gaps and incorrectness. This assessment is then propagated into an AQG which finally produces another set of questions based on the gaps identified.

5. The knowledge source contains information about the domain of interest. The knowledge source could be structured (eg. ontologies) or unstructured (eg. text).

Several techniques for implementing adaptive learning systems have been developed. In the following section, we will investigate different ontology-based and non-ontology-based adaptive learning techniques.

2.1 ONTOLOGY BASED TECHNIQUES FOR ADAPTIVE LEARNING SYSTEMS

Ontologies provide a formal and explicit means of defining the concepts, properties, and relationships that exist within a specific domain. They have numerous applications, particularly in educational settings, as they facilitate shared understanding between individuals and software agents regarding the underlying knowledge structure. Additionally, they promote knowledge reuse by eliminating the need to create an ontology from scratch if a pre-existing one is available for use in modelling the domain at hand [13]. Kwasnicka, H. [13] propose an ontology for personalised learning. The ontology consists of classes relating to the educational resources required to learn, such as the courses, concepts, resources, and so forth. Embedded into the ontology is a learning style class that represents each student's learning style and uses the Felder-Silverman Learning Style Model (FSLSM) [14]. There were two reasons for this choice. Firstly, one can easily establish a learners learning style (visual, audio, or writing/reading) and can easily be linked to an e-learning system. Secondly, the FSLSM can be used in many different adaptive environments. The FSLSM is also suitable for STEM (Science, Technology, Engineering, Mathematics) [15].

2.1.1 PERSONALISED ADAPTIVE ENGINE

Boyinbode, O. [15] implements an ontology into a web based application for personalised e-learning. It aims to provide the appropriate learning materials to learners based on their learning style, preference, background knowledge, and personal profile. Like Felder, R.M. [14], Boyinbode, O. [15] uses a FSLSM for similar reasons as stated above. It makes use of Web Ontology Language (OWL), a semantic web language that represents knowledge about things and relationships between them. The OWL file produced by the protégé tool extracts concepts or classes from a domain ontology. The ontology-based adaptive system in [15] consists of several major components. The most important being the Personalised Adaptive Engine.

The Personalised Adaptive Engine is in charge of supplying individualised learning content based on the learner's model, which is accomplished by combining instruction items to form organised content.

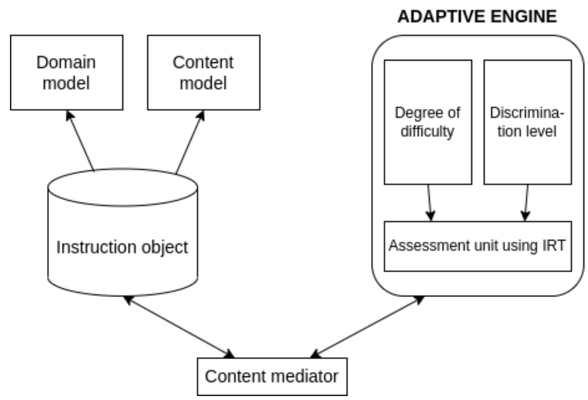

Figure 3: Architecture of the Personalised Adaptive Engine and Domain ontology as shown in [15]

It collects information about the learner and learning objects through intermediaries and regularly tests knowledge and abilities. The item response theory is used to evaluate performance [16]. Item response theory is a model-based approach for selecting appropriate learning items based on an analysis of the relationship between a learner's abilities and their responses to the items. It works on the premise that the likelihood of a correct response to an item is determined by personalized and itemized variables, and it uses this information to determine the best learning items for the learner. To test the performance and effectiveness of the model, two test methods were conducted. The first method individual learners were given was an assessment to evaluate their performance and track their learning progress over a set period of time. The second method, a General Study Course (GNS), was used as the learning material to test the personalised adaptive e-learning system. The results proved that the mean performance of the personalised adaptive system was higher than that of the conventional. Overall, this system proved to be effective and does a really good job of delivering personalised content for each learner. However, it is limited to the content available in the content model and does not have the ability to generate new, original, and unique content. Limiting yourself to content within your content model provides no opportunity to eliminate knowledge gaps altogether. Having the ability to automatically generate new questions related to a particular subtopic in the domain can help further improve the learner's understanding of the work. It would also prove more beneficial to more knowledgeable students, as it would prevent them from boredom with the system and test their extremities.

2.1.2 LEARNING PATHS

Karampiperis, P., and Sampson, D. [17] aim to improve the existing system of the Adaptation model. The Adaptation model contains a set of rules to adaptively select and sequence learning resources. They propose a different method of adaptation by generating all possible learning paths first and thereafter, selecting a suitable path. Learning paths are contained within a Learning Paths Graph (LPG).

A LPG is an acyclic directed graph and represents all the possible sequences of learning resources, or learning paths, that align with the learning goal at hand [17]. A LPG uses a CPF (Concepts Path Graph), a graph that represents the structure of a Domain Concept Ontology about the learning goal, for construction. A Domain Concept Ontology is used as it provides a structured way of representing knowledge. A suitability function, a function for estimating the suitability of a learning object for a learner, is then added as a weight for each connection in the LPG. Each weighting is the inverse of the suitability of a learning object. Therefore, when looking for a suitable learning path for a learner, the LPG uses a shortest path algorithm. The quality of the model was tested by comparing the production of the learning paths to the ideal learning path. The results of the new method Adaptation model performed well, and in most cases, it accurately produced the correct sequence of learning objects (learning paths). However, this accuracy diminishes as the domain of the concept of knowledge broadens. As the concept area broadens, the Domain Concept Ontology hierarchy increases. Therefore, the sequence of learning objects produced by the LPG increases. A longer sequence of learning objects introduces more mismatches and, as a result, reduces the accuracy of the model. Ultimately, achieving scalability on this type of model using a Domain Concept Ontology will be challenging.

2.2 NON-ONTOLOGY BASED TECHNIQUES FOR ADAPTIVE LEARNING SYSTEMS

2.2.1 NEURAL NETWORKS

Neural networks originate from studies relating to biological nervous systems, particularly the human brain [18]. It consists of many interconnected processing units referred to as nodes. These nodes mimic the functions of neurons in the human brain. Neural networks' processing power lies in the weighted links that connect these nodes [19]. A neural network takes inputs and produces an output. The inputs are the weighted links and are the parameters that the neural network uses to learn [18]. When an output is produced, its error is examined; that is the difference between the predicted value and the expected value. The weighted links are then fine-tuned in each pass through a neural network until the output has been optimised. Neural networks are typically used for problems relating to classification and forecasting [19].

Kwasnicka, H. [20] presents a study done on an intelligent agent called Learning Assistant, which uses an external tool called a SOM (Self Organising Map) to train a neural network. The Learning Assistant is embedded into WebTeacher, an e-learning environment. The purpose of the study was to create a personalised learning path for each pupil. Learning Assistant consists of two modules, an AI assistant and a SOM neural network. The SOM neural network is responsible for clustering or classifying pupils with similarities into groups. It does so by taking input examples and building a map. The map consists of many different clusters that represent similar students. The AI assistant is used to develop a personalised individual plan for each learner. The input into the AI assistant is unstructured metadata with information about pupils and the learning content. A learning path is then generated for each cluster, and each learner will receive their learning path, depending on which cluster they lie in. It's important to note that a learning path in this context consists of a unique set of educational materials or a study program for learners in a particular cluster. The results proved promising among lower graded students while making no difference for higher graded students. The biggest weakness of this research study was the use of weak didactic materials. Firstly, weak didactic materials come with the possibility of having incorrect or incomplete information about the content. This could affect learner understanding, which affects the results of the knowledge base. With this approach, you are most likely exposed to having more gaps in the content. Secondly, having unstructured metadata makes the content and the relationships about the content more difficult to understand and process. It would also make it more difficult to manage or add more content. Finding knowledge gaps for students using an unstructured data source would be more difficult than using structured data such as an ontology. There is an argument to be made that unstructured knowledge could cover a broader domain; however, the researchers experimented on Computer Science students, concerning a small subtopic.

2.2.2 GENETIC ALGORITHMS

Genetic algorithms (GAs) are search algorithms that evolve solutions to problems using natural genetic principles. While a genetic algorithm is frequently used as an optimization technique for determining a function's optimum solution, it has additional possible applications. A GA can be beneficial for other use cases that require robustness and global optimization [21]. A chromosome population represents potential solutions to the problem, and the population evolves over time through competition and variation. In the selection process, the fitness of each chromosome determines which chromosomes are used to form new ones. To create new chromosomes, genetic operators such as crossover and mutation are used [22].

Huang, M.J. [21] uses a GA along with case-based reasoning (CBR) to develop curriculum materials that are appropriate for each learner's needs and help them learn more effectively in a web-based environment. It achieves this by designing a system called, The Personalised E-Learning System based on Mastery Learning (PLS-ML). The GA module includes a generation engine and an XML-based knowledge description, whereas the CBR module includes a knowledge base. The main focus of this section is adaptive learning algorithms; hence, we will be focusing on the GA module. It is responsible for generating a personalised learning path and does so through several steps.

There are a few important concepts that need to be taken into account in Figure 4. Firstly, selecting an initial population size could be tricky. Increasing the population size of the GA will decrease the search speed, but it will increase the likelihood of discovering a high-quality solution. Secondly, and most importantly, selecting an appropriate fitness function is crucial. The fitness function assesses the quality of the GA-generated learning path. Pre-test results, curriculum difficulty levels, and concept relation degrees must all be taken into consideration when designing a learner's personalised learning path. In this approach, the learning path produced by the GA only considers the curriculum for which the learner provides incorrect pre-test results.

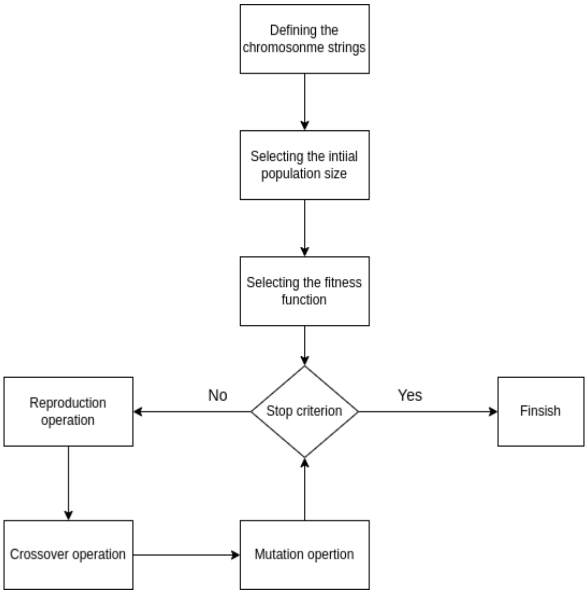

Figure 4: Process of the genetic algorithm used in [21]

The first curriculum in the designed learning path is chosen based on its degree of difficulty. Lastly, the stopping criterion determines how many times the GA has to run through the cycle of: reproduction, crossover, and mutation. The experiments conducted in [21], the stopping criterion was set to 100 generations.

Four tests were performed on the PLS-ML system, the most important being the global test, which verifies the overall performance of the system. The system proved successful at correctly diagnosing each learner's weakness in the curriculum when they have answered a question incorrectly. The PLS-ML takes into account both the difficulty level and the continuity of subsequent curricula, allowing for personalised curriculum generation during the learning process. The PLS-ML does not use ontologies as a knowledge description but an Extensible Markup Language (XML). Like ontologies, XML is also structured in a hierarchical manner and can both be interpreted by machines and humans. However, it lacks the formal semantics and reasoning capabilities of ontologies making it more difficult to identify relationships between concepts. Another advantage that ontologies have over XML is that they produce more accurate and efficient artificial intelligence systems.

3 DISCUSSION

In Section 2, four techniques to implement an adaptive learning system were critically analysed. Each of these techniques presents its own unique approach, which carries its own advantages and disadvantages. It was possible to group the four techniques into two groups. The first group being techniques that use an ontology as their input knowledge source. The second group were techniques that never used an ontology. It is important to note that even though an adaptive learning system does not use an ontology, that does not mean that it uses unstructured knowledge. Structured knowledge is data that has been organised and formatted in a way that makes searching for it efficient. For example, XML files or knowledge graphs.

The two techniques that utilised ontologies were a Personalised Adaptive Engine [15] and Learning paths [17]. Both techniques showed promising results that provided personalised learning resources to each learner based on their level of knowledge, learning style, and preferences. However, [15] proved to be an overall technique for implementing an ontology-based adaptive learning system. The main factor favouring [15] over [17] is the problems [17] presents when a broader domain of knowledge is used. The system of [17] becomes much more limited in its full capability and becomes unreliable. If the learning path becomes less reliable, it could generate inaccurate learning materials and not produce the necessary resources needed by each learner to better understand the content. However, even though [15] does not produce issues of scalability, similarly to [17], it does not generate new and unique learning materials; rather, it searches for existing material in the knowledge source and presents the materials accordingly. As presented in Figure 1, CAT [11] has the ability to integrate an adaptive system with an AQG, which allows it to generate unique learning materials and broaden the learner's understanding of the concepts.

The adaptive learning systems that utilised other forms of structured or unstructured knowledge, that is, knowledge that was not ontologies, as a knowledge source were Neural Networks [20] and Genetic Algorithms [21]. Both of these techniques were implemented in a web-based environment. Although both techniques produced promising results by producing an appropriate curriculum and learning materials, they generally presented more gaps in their systems than the ontology based systems. Kwasnicka, H. [20] used unstructured knowledge as an input into the neural network. Although this has the advantage of being able to cover a broader knowledge domain, it makes it more difficult to identify what the gaps in the learners' knowledge are. Furthermore, the use of low quality didactic materials to test the system could allow incomplete or incorrect information about the content, directly affecting the learning materials presented to the learners. The technique that utilised genetic algorithms [21] performed promisingly and was equally as good as [20]. One major flaw in [21] is that it only considers the curriculum for which the learner provides incorrect pre-test results. Although this approach will help them improve their knowledge of that particular concept, a problem arises if learners guess the correct answer to the pre-test and completely bypass a concept that they do not entirely understand. However, the GA tries to mitigate this risk by implementing a function that calculates the degree of correlation between concepts, which means that if a learner does not understand a concept, the GA will develop a curriculum not only with that concept but with similar concepts too. Furthermore, [21] is the only technique that attempts to generate new and unique learning materials for each learner out of the four techniques.

All four techniques seem to successfully generate unique educational materials for each learner in an attempt to close a knowledge gap they might have. However, only one technique, GA [21], attempts to produce new content outside of its content model. Having the ability to generate new content for each learner is a fundamental requirement that the ontology-based adaptive learning system we propose should possess. However, [21] does not use an

AQG in their model, another system that is crucial for generating questions from the content in the ontology. From these observations, it is clear that all the techniques discussed achieved one of our many goals for our adaptive learning system, which is to generate educational materials for each learner to close knowledge gaps. However, all four techniques failed to implement a question generation system within their model to generate unique educational resources, one of our main goals for the proposed adaptive learning system.

Overall, the techniques that proved most applicable to our proposed solution of developing an adaptive learning system are the Personalised Adaptive Engine [15] and the Genetic Algorithms [21]. The reasons being the Personalised Adaptive Engine provides a starting point for how to integrate an ontology with an adaptive learning system, whilst the Genetic Algorithms provide insight into how core concepts are related and how this information can be used to generate a set of unique educational materials.

4 CONCLUSIONS

In this literature review, we have identified two problems with most modern e-learning platforms. Firstly, it does not help learners who have knowledge gaps in a specific topic, as all learners are presented with the same learning materials. Secondly, the lack of customizability of modern e-learning systems causes learners to lose interest in using e-learning systems as they find the content less challenging. The problems of static e-learning systems could be solved by using an adaptive learning system. This would present unique learning materials to fill in knowledge gaps and help learners better understand concepts. Furthermore, it was established that a domain ontology would be best suited as a knowledge source for our proposed adaptive learning system, as it proved more advantageous than any other structured or unstructured knowledge source discussed. Four techniques to implement an adaptive learning system were critically analysed. These four techniques were: Personalised Adaptive Engine, Learning Paths, Neural Networks and Genetic Algorithms. All these techniques managed to generate educational materials for each learner to fill in knowledge gaps. However, none of these techniques presented a system capable of producing new quality content outside of their content model. Moreover, none of the four techniques utilised or featured an AQG in their system.

Therefore, the integration of an adaptive learning system and an AQG, such as CAT, is a gap that could be filled in the e-learning platform with our proposed ontology-based adaptive learning system.

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