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Summary

The main goal of the research work is to develop an intelligent E-tutoring framework with the integration knowledge explore ontology.

In the research work, I have contributed to the development of the extended ITS architecture and based on this experience I later developed the adaptive ITS architecture based on the current research directions and trends presented in the previous work. Besides the standard models, the proposed architecture includes a common shared database and knowledge-based background. The advantages of the shared database are to share a common understanding of the knowledge structure, reuse the knowledge, and mix different knowledge bases.

In my research work, I have developed a novel model for the purpose of enhancing the learning and teaching processes in 3 ways. These models are the ontology-based model to support the learning process in LMS, the ontology-based Knowledge domain model for the IT domain in E-tutoring systems, and the ontology-supported domain knowledge module for an E-tutoring system. The main goals of these models is to enhance the learning and teaching process, support recommendations, generate hints, automatically support the generation of problems and solutions, and automatically support the generation of new material.

In the first model, depending on the properties of the learning materials, two types of ontologies are implemented as a form of general concepts: domain knowledge ontology and specific domain knowledge ontology. These modules represent the knowledge to be learned, deliver input to the expert model, and eventually provide detailed feedback, select problems, generate guidance, and support the student model. The introduced domain knowledge model is based on the current research directions. The presented model stores the topics, concepts, attributes, tasks, competencies, assessments, and relations. To facilitate the sharing and reusing of the domain knowledge model features in E-tutoring systems, ontologies are utilized to organize and represent the domain knowledge model. The benefit of this model is to personalize the learning materials for learners.

This research developed and presented a novel domain knowledge model for teaching materials using ontology as a knowledge representation technique. In addition, the presented model allows the knowledge construction for tailoring the explanation of tutoring material through the information gathered in the learner model. The primary purpose is to construct a general and flexible knowledge model. However, flexibility means allowing for extensions and modifications of the core model. In other words, flexibility also refers to using the knowledge model in different domains and allowing a dynamic and automated framework.

There are many types of knowledge forms in the literature, this work focuses on procedural knowledge and declarative knowledge. Declarative knowledge deals with the selected model's facts, methods, and practices. Procedural knowledge deals with the problem-solving process. Combining the declarative and procedural knowledge to add functionality to the proposed model and provide access to existing domain-specific glossaries, taxonomies, and ontologies is preferred to build the domain knowledge model. A well-designed structure for the knowledge domain requires adopting a proper methodology, especially in ontology representation, because

it provides a suitable form for learning material representation. The presented model can be used effectively for the intelligent processing of teaching material and form a base for interaction and collaboration supporting E-tutoring framework components. Using an ontology, we efficiently can reuse the knowledge domain stored on it.

The formal description of the proposed model is based on a fundamental concept element, denoted as a knowledge unit covering the specific teaching and competency dependency units. Many types of relationships are introduced between the knowledge units in the domain ontology. The core components of the suggested model are knowledge unit, knowledge slot, task unit, material unit, rule unit, and educational unit. The domain are Loops in the C++ programming language is selected as knowledge field for testing the suggested model. The proposed model is introduced to explain how the ontology domain knowledge model can be combined with an E-tutoring system to improve the quality of intelligent problem-solving. This solution, make it possible to reuse knowledge components, and it can serve to enhance the teaching and learning process. The problem of isolated knowledge bases can be avoided using ontology as a knowledge representation technique for building the domain knowledge model. The developed ontology can be involved in managing adaptive intelligent e-learning frameworks in the future. The domain ontology knowledge model considered in chapter 3 has various pedagogical goals. These goals include understanding specific domain facts and solving standard problems, obtaining a conceptual and intuitive understanding of the material in the selected domain, and learning general problem solving and metacognitive skills. A significant feature of the selected model is that the knowledge representation techniques have a standard structure. This standard structure allows general representational inference tools and control mechanisms, facilitating the pedagogical analysis of knowledge.

The researcher used some technologies that deal with adding the functionality by implementing and integrating the knowledge domain model mentioned in chapter 4. with an E-tutoring framework. Regarding the domain knowledge model implementation for an E-tutoring system and the ontology as a back end, Python programming language, Python Flask web framework module, and the Owlready2 module are used. Python offers different libraries for the Owlready2 module for querying the knowledge stored in the domain ontology, such as RDFLib, SPARQL-Client, and SPARQLWrapper. In querying the model, RDFLib and SPARQLWrapper are used. The Flask framework is used to develop the prototype system to integrate the constructed ontology for the selected domain knowledge model with the E-tutoring framework.

For evaluating the prototype system which is integrated with the ontology domain knowledge module functional test was done several task assessments were performed. According to the experiment the result gives correct feedback according to the user answer showing if the answer is correct or incorrect and offering suggestions. The suggestion related to unit name, task name, task question, learner answer, the result, suggest reading material and the task score.

As a result, the developed ontology domain knowledge model integrated with the prototype system can be used in managing adaptive intelligent E-learning frameworks in the future. Furthermore, the domain ontology knowledge model can meet various pedagogical goals. These goals include understanding specific domain facts and solving standard problems, obtaining a

conceptual and intuitive understanding of the material in the selected domain, and learning general problem solving and metacognitive skills. A significant feature of the selected model is that the knowledge representation techniques have a standard structure. However, the standard form of the proposed model can allow for general representational inference tools, control mechanisms, and facilitating pedagogical analysis of knowledge. In addition, combining the proposed ontology domain knowledge model with an E-tutoring system can enhance the quality of intelligent problem-solving. Also, it will be possible to reuse the knowledge domains. Finally, a proposal of the domain knowledge model for the E-tutoring system can enhance the teaching and learning process, support recommendations, generate hints, and automatically support the generation of problems and solutions.

For managing the uncertainty of students' knowledge and identifying their status in learning the domain knowledge model in an E-tutoring framework, we used Intuitionistic fuzzy logic values (IFVs) to represent the student knowledge level in the domain knowledge model database. The main goal is to evaluate learner knowledge based on an accumulative task assessment using question-and-answer pairs and updating a student model. IFVs is used for calculating student knowledge level by means of which the system can automatically recommend further reading materials/tasks.

Combining the domain knowledge model with E-tutoring systems can enhance the quality of intelligent problem-solving. Also, it will be possible to reuse the knowledge domains. Finally, the domain knowledge model for E-tutoring systems can improve the teaching and learning process, support recommendations, generate hints, and automatically support the generation of problems and solutions.

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1 Introduction

Intelligent Tutoring System (ITS) is a computer system that use artificial intelligence techniques to improve and customize automation in education. ITS differs from other educational systems because it uses a knowledge base to guide the pedagogical process. This tends to promote the mastery of the student's domain knowledge by managing the generation of new problems, topics, and instruction / feedback. So that the development of an ontology domain knowledge model for intelligent E-learning systems have a great chance to provide high-level services for the learners.

The goal of this research is to develop a novel ontology domain knowledge model for intelligent E-learning systems (E-tutoring systems) and detect the student's knowledge level status when they use the system and prepare the material according to their status.

The research will focus on developing ontology domain knowledge model and student knowledge model for E-tutoring systems to enhance teaching and learning process and make the learning between the learner and the system as one-to-one tutoring. Ontology offers a common vocabulary which can be used to model various domains including the type of object, related concepts, and their properties and relationships. However, understanding knowledge level status of students are key features of their success or failure in their studies. For educational environment, there is a performance-based requirement that verifies student learning.

1.1 Methodology

This research aims to enhance the quality of the teaching and learning process by making it personalized. The process design and development of domain ontology usually encompasses several standard tasks. However, there is no dominating approach for constructing ontologies. The main principle is to define the ontology concepts related to the objects and the relationships for the selected domain. The methodology for creating and building an ontology assumes defining the objectives and domain of applicability. In addition, this methodology must identify the steps in higher-level detail: the purpose of designing the domain ontology, the types of questions that should be answered through it, and how it will be utilized and supported for solving the problem for the selected domain. Several techniques for the design and development of ontology are given, such as [7] and [8]. Though these methods are somewhat different and influenced in varying ways by the technology used, the underlying processes of developing the domain ontology are similar. Therefore, the suggested ontology development process is composed of the following phases:

- Define the domain and purpose of the ontology.
- Discover if there are related ontologies.
- Enumerate essential terms in the domain.
- Define the key classes and their hierarchy.
- Identify the properties of classes.
- Facets attaching to properties.
- Create class instances.

2 General Background

2.1 Introduction

The domain model in ontology engineering is a formal representation of the domain knowledge with concepts, roles, individuals, datatypes, and rules, usually based on description logic. Moreover, it contains machine-readable definitions of elementary concepts in the domain and their relationships, allowing sharing of a common understanding of the information structure among people and software agents and the reuse of domain knowledge [1]. Thus, ontologies are considered a fundamental method for knowledge representation, particularly in intelligent E-learning or intelligent tutoring frameworks [1].

Researchers need to consider a common type of architecture and models of intelligent tutoring or E-tutoring systems to match existing standards and support reusability, standardability, flexibility, and interoperability, which remains a challenge for adaptive learning systems [2].

The rapid development of communication and information technologies has offered new possibilities and challenges in multiple disciplines. One of these areas is education domains. Online education provides several advantages: convenience, reduced costs, and ease of taking courses. As a result, many institutions have adopted E-learning platforms in recent years. Furthermore, it has proven effective and efficient for enhancing learners' knowledge. The most appealing feature of an E-learning platform is that it provides flexible learning paths based on learners' skills and abilities. Therefore, teaching materials can be stored and managed more flexibly as learners can choose where and when to learn them based on their individual needs.

Today, new challenges and innovative technologies are faced in the education discipline. However, the vital area of innovative technologies presented lies in the learning process. Therefore, it becomes required for instructors to integrate new directions and methods into the educational process. One such aspect that came into reality is the intelligent tutorial system. The next points deal with details about E-learning and intelligent tutoring systems.

The E-learning platform is becoming increasingly popular in the academic community due to many learning benefits achieved through learning anywhere, anyplace, and anytime. However, it tends to be most used for web-based training to access online courses. One possible reason for lack of success is that it does not practice just by putting lecture notes on the internet. Learning tools such as intelligent tutoring systems (ITS) can improve this situation. ITS incorporates expert systems to monitor a learner's performance and customize instruction based on adaptation to the learner's learning style, existing knowledge level, and appropriate instruction plans in E-tutoring systems. Learning environments rapidly change from traditional to information technology (IT) in the teaching space. In earlier decades, researchers studied how IT technology as a learning tool affects learning performance.

New computer-aided instruction paradigms have emerged during the rapid expansion of internet technologies. These technologies have started from learning management systems, Massive Open Online Courses, and reaching to adaptive learning for intelligent education. Figure 1 illustrates the historical evolution of education technologies in E-Learning environments from the 1990s until now [3].

With continuous technological development, different institutions employ and widely exploit many aspects and tools. The tools are blended learning, gamification, microlearning, personalized learning, and continuous learning [4]. Blended learning is the learning process combining two or more learning methods, such as pedagogical and web-based technologies. Gamification is a process of adding some gaming elements to engage learners in the learning process. Microlearning refers to the learning process of teaching materials presented in chunks, sections, or parts in short and measurable periods of time. In microlearning, the learners can proceed to learn the next content or part after completing the previous part. Personalized learning enables learners to choose or customize their learning materials based on pedagogical differences. Finally, continuous learning or lifelong learning refers to the ongoing and voluntary pursuit of knowledge and expertise for personal or professional purposes.

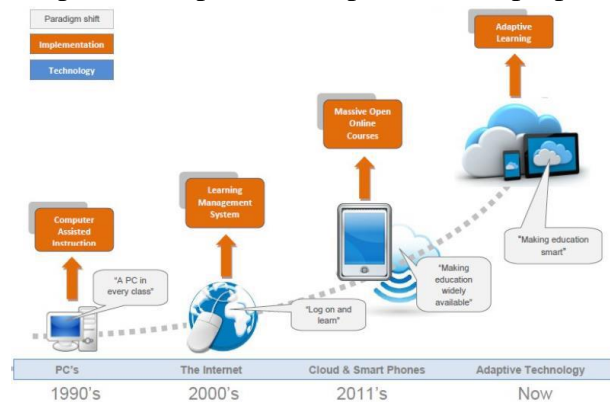


Figure 1 Historical evolution of education technology [3]

Nowadays, the use of technology to enhance education and learning is rapidly expanding. Intelligent Tutoring Systems (ITS) is one of the technologies for improving teaching and learning that represent a new way of computer-based training using artificial intelligence techniques. The system uses a knowledge base to provide feedback to the student as the student interacts with the system.

3 Formal Logical Ontology Model for an E-tutoring System

Many investigations in artificial intelligence (AI) and information science disciplines have focused on ontology. Ontology has emerged as a critical component of the semantic web, including many knowledge domains. Although many domain fields require ontologies, creating domain ontologies remains a big problem in the forms of design and execution. Information Science (IS) is one field in which a unified ontology model is required to simplify information access across diverse data resources and share a common understanding of domain knowledge.

The primary purpose of this research is to construct a general and flexible ontology domain knowledge model, which can be integrated with an E-tutoring system platform. Flexibility means allowing for extensions and modifications of the core model. Flexibility also refers to using the knowledge model in various domains and a dynamic and automated framework. Moreover, flexibility refers to the ability of the system to respond to any potential developments without affecting its value performance.

3.1 The Ontology Domain Knowledge Model for Teaching Materials

The domain knowledge model requires information about the study domain and teaching materials associated with the knowledge topics covered through the tutoring session [5]. The purpose of the domain knowledge model is to represent the knowledge content of an E-tutoring system. The domain knowledge model is used, among others, for storage, construction, and description of the learning material. The representation of the domain knowledge model is related to the semantic model of the teaching materials. A semantic model (SM) is a higher level of semantic-based representation and structuring formalism for the ontology database. SM specification describes an ontology database regarding the types of knowledge units in an E-tutoring framework, the classifications and groupings of those knowledge units, and the structural relations among them. SM provides a group of higher-level modeling principles to understand knowledge unit relations semantics in an E-tutoring application framework. In ontology engineering, semantic modeling has been implemented to create different learning knowledge units [6]. Semantic refers to the representation of knowledge unit meaning with symbols. Semantic modeling has been used to make sense of knowledge concepts, relationships, and what they represent in an E-tutoring system knowledge model [6]. The semantic model differs from conceptual data modeling, physical data modeling, logical data modeling, and modeling process rules in many aspects. The difference extensively depends upon the specific knowledge unit use case and the desired objectives from each knowledge unit use case [6]. Semantic modeling is applied to describe the relationships between specific types of data. Modeling is the method of categorizing knowledge for community use. Modeling keeps this in three forms: It provides a framework for human communication, a means for demonstrating conclusions, and a structure for controlling different types of knowledge. Semantic modeling is a continuous process for representing knowledge. The knowledge should be well-structured and understandable, and these structures can be represented in the modeling language.

Teaching materials are one of the essential educational and learning activities and components. In addition, the instructor can use teaching materials to support students in learning a knowledge domain through textbooks and visual or audio knowledge. Therefore, well-formed teaching materials will significantly strengthen and provide the primary purpose of students for learning the knowledge unit and their interest in the domain knowledge model.

Tutors promote the development of distinctive styles of teaching materials according to further requirements to support individualized and adaptive learning. However, traditional methodologies for designing teaching materials are time-consuming. To speed up the teaching materials' development process, we can use a modern approach based on the knowledge model's automatic generation and generalize and make it flexible. Consequently, due to the ongoing development of the technologies and knowledge domain requirements, scholars must be robust and try to produce a vast knowledge model for the teaching materials and make them available on the E-tutoring system.

3.2 Knowledge Model

A human's mental knowledge commonly begins with notifying and recognizing, and mental representation is contacted upon to build knowledge. In artificial intelligence, solving user needs requires a knowledge model consisting of all facts related to the problem domain and a way to manage the knowledge representation for obtaining the solution. For better results, knowledge should systematize sufficiently. There are two fundamental forms of knowledge: procedural knowledge and declarative knowledge.

Declarative knowledge (ontology), sometimes known as formal or descriptive knowledge, refers to information or facts held in the memory [7]. Declarative knowledge manages the actual or conceptual knowledge related to a human. In ontology, declarative knowledge relates to the aspects of material and strategy for the knowledge domains. It is a static description that captures the real world by interpreting concepts. Declarative knowledge, also called explicit knowledge, represents and explains textual, graphical, or verbal representation structures [8]. Because declarative knowledge deals with the study of facts, methods, techniques, and practices, it can be displayed, reported, and reproduced in the form of information to become clear knowledge assets. Declarative knowledge represents facts, events, operations, and relationships to a given domain. The combination of procedural knowledge (behavioral model) and declarative knowledge (ontology) provides access to existing domain-specific glossaries, taxonomies, and ontologies preferred to build the domain knowledge model.

Procedural knowledge (behavioral model) is a type of knowledge covered in different scientific disciplines and requires different techniques for its enhancement. This knowledge indicates production and is formed by preparing for the problem-solving approach [9]. In addition, procedural knowledge can be a procedure for a sequence of steps performing some activities to reach the target task [9]. Procedures are recognized by applying skills, strategies, results, and internal actions [9]. These procedures can perform in the way of algorithms, a predefined flow of actions, which leads to a successful response when done correctly, and potential actions that must sequence the problem-solving procedure (like equation-solution steps).

A well-designed structure for the knowledge domain requires adopting a proper methodology, especially in ontology representation. There are comprehensive study guidelines and frameworks for ontology building, development, and maintenance. I suggested an ontology knowledge domain model for an E-tutoring platform, which provides a suitable form for learning material representation. The presented model can be employed effectively for intelligent processing of teaching material and can form a base for interaction and collaboration supporting E-tutoring framework components. For knowledge representation, the ontology approach can be used. Ontology is a good representation schema because it is common and describes the concept, knowledge, facts, properties, and relationship standardly. Using an ontology can reuse the knowledge domain stored on it. The suggested model can support solving the limitations of existing models.

3.3 Knowledge Representation Scheme

Knowledge Representation uses symbols to represent a collection of facts inside a knowledge domain to facilitate inferring facts to construct a new knowledge element. Knowledge representation plays an essential part in the artificial intelligence discipline. Knowledge representation is a technique applied in a computer software structure to define the knowledge base and allow AI mechanisms to perform well. In software design, representation of knowledge and manipulation has drawn an excellent deal of concentration since the earlier days of the computer science domain, resulting in various Knowledge Representation schemes. In addition, the Knowledge Representation scheme should be able to represent structural and relational knowledge naturally.

Although many kinds of knowledge representation (KR) schemes are found in the literature, two types are widely used, including single and hybrid KR schemes. The single schemes deal with the structured knowledge representations, and hybrid schemes integrate two or more single KR schemes. Single representation schemes represent the knowledge in the form of a graph. Accordingly, they are suitable for representing structural and relational knowledge. Single schemes involve several KR techniques: semantic networks, frames, knowledge graphs, ontologies, rule-based, case-based, logic-based and belief networks.

3.4 Evaluation of existing knowledge models

Table 1 displays a comparison according to some criteria or features for the suggested model with others in the literature. These features covered reusability, standardability, flexibility, open knowledge, simplicity, reasoning engine, and uncertainty.

These features are the main requirements in implementing an efficient ITS systems, I used these features in this comparison because they are the most important features in developing a standard domain knowledge model. I focus on solving this issues and propose a general model to cover the goals of supporting the teaching and learning process. These goals include understanding specific domain facts and solving the task activities in learning, obtaining a conceptual and intuitive understanding of the material in the selected domain, and learning general problem-solving and metacognitive skills. A significant feature of our model is that the knowledge representation techniques have a standard structure. However, this standard structure allows us to apply general representational inference tools and control mechanisms in order to facilitate the pedagogical analysis of the knowledge domain.

Table 1 Comparison of the knowledge representation models

| | Reusability | Standardability | Flexibility | Open knowledge | Simplicity | Reasoning engine | Uncertainty |
|-------------------|-------------|-----------------|-------------|----------------|------------|------------------|-------------|
| Knowledge graph | √ | √ | × | √ | × | √ | √ |
| Semantic networks | √ | √ | × | √ | × | √ | √ |
| Rule-base | × | √ | × | × | × | × | √ |
| Case-based | × | √ | × | × | × | √ | √ |
| Bayesian Network | × | √ | × | × | × | × | √ |
| Frame-based | √ | √ | × | √ | × | × | × |
| Logic-based | √ | √ | × | × | × | √ | √ |
| Ontology-based | √ | √ | √ | √ | √ | √ | √ |

√ Means the feature is allowed, and × means the feature is not allowed.

Most ITS systems developed in the literature focus on solving a single domain. They try to create only single courses like introduction to computer programming tutor and Java object tutor. Most of them use isolated knowledge bases, and these local knowledge bases can provide only limited knowledge background. The limitations of the local knowledge bases are lack of reusability, lack of standardization, lack of flexibility, simplicity, reasoning engine, uncertainty, and it has limited knowledge base.

3.5 The Adaptive E-tutoring System Architecture Model

Based on the current research directions and trends presented in the previous work, I propose an adaptive E-tutoring system architecture shown in Figure 2. Beyond the standard models, the proposed architecture also includes a common shared database and knowledge-based background, too. The advantages of the shared database are to share a common understanding of the knowledge structure, reuse the knowledge, and mix different knowledge bases. Furthermore, ontology delivers a shared language in knowledge databases, which can model different domains, including the type of entities, related concepts, their properties, and relationships.

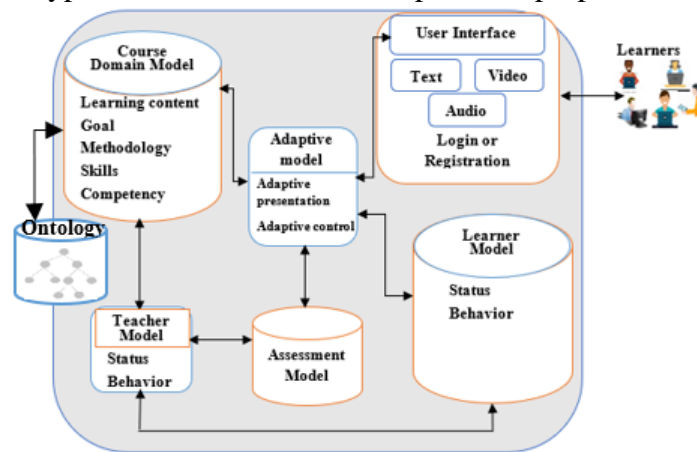


Figure 2 Adaptive Architecture

3.6 The Proposed Ontology Domain Knowledge Model Concepts

In my research work, I have developed a model for the purpose of enhancing the learning and teaching processes in 3 ways. These models are the ontology-based model to support the learning process in LMS, the ontology-based Knowledge domain model for the IT domain in E-tutoring systems, and the ontology-supported domain knowledge module for an E-tutoring system. The main goals of these models are create general and flexible model to enhance the learning and teaching process, support recommendations, generate hints, automatically support the generation of problems and solutions, and automatically support the generation of new material.

3.6.1 Ontology-based Model to Support Learning Process in LMS

In this work, an ontology-based model is introduced to facilitate the Learning Management System (LMS) in the learning processes (LPs) [10]. The suggested domain ontology model is a general framework, and the main goal is to discover the behavior of learners and cover the entire learning process (LPs) and its components. To support the LPs, I developed an ontology model

to define a set of relationships that would be sufficient and clear to represent all relationships for building the ontology model. The presented model structure contains three layers of LPs, the top layer architecture, the conceptual layer architecture, and the course ontology model architecture. The goal of the top layer architecture is to define a general framework of LPs to the learners as shown in Figure 3. This contains knowledge unit, learning module, presentation unit, presentation form, evaluation form, model of learning, and interface components.

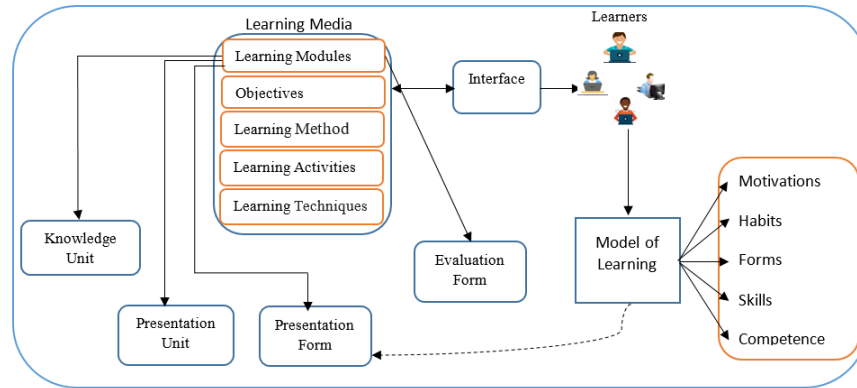


Figure 3 Top layered architecture [10]

The conceptual model layer is to define the framework of the actual process of LPs to the learners displayed in Figure 4. This framework contains four components knowledge unit, presentation unit, presentation form, and evaluation form.

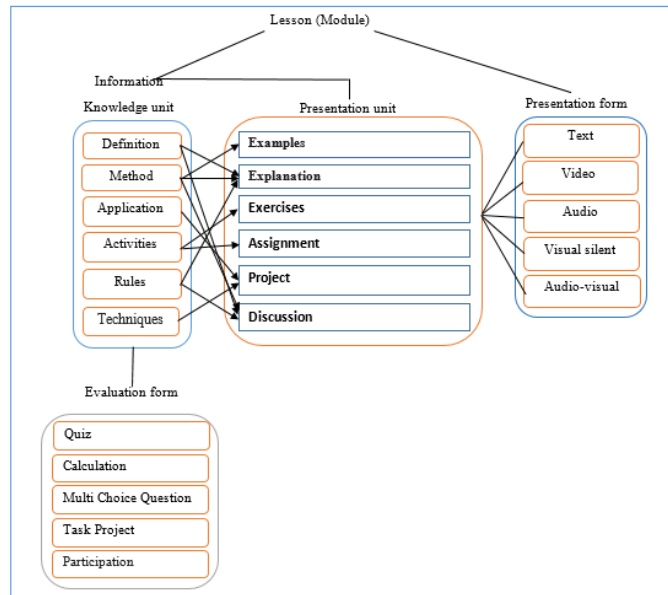


Figure 4 Conceptual model layers [10]

The course ontology model refers to a course in the education domain. The objective of this model is to define the domain ontology model of the course ontology. The model consists of the students, the teacher, and the primary components of a course such as learning objectives, teaching methods, learning contents, learning media, and assessment, and then the other components of the course structure displayed in Figure 5.

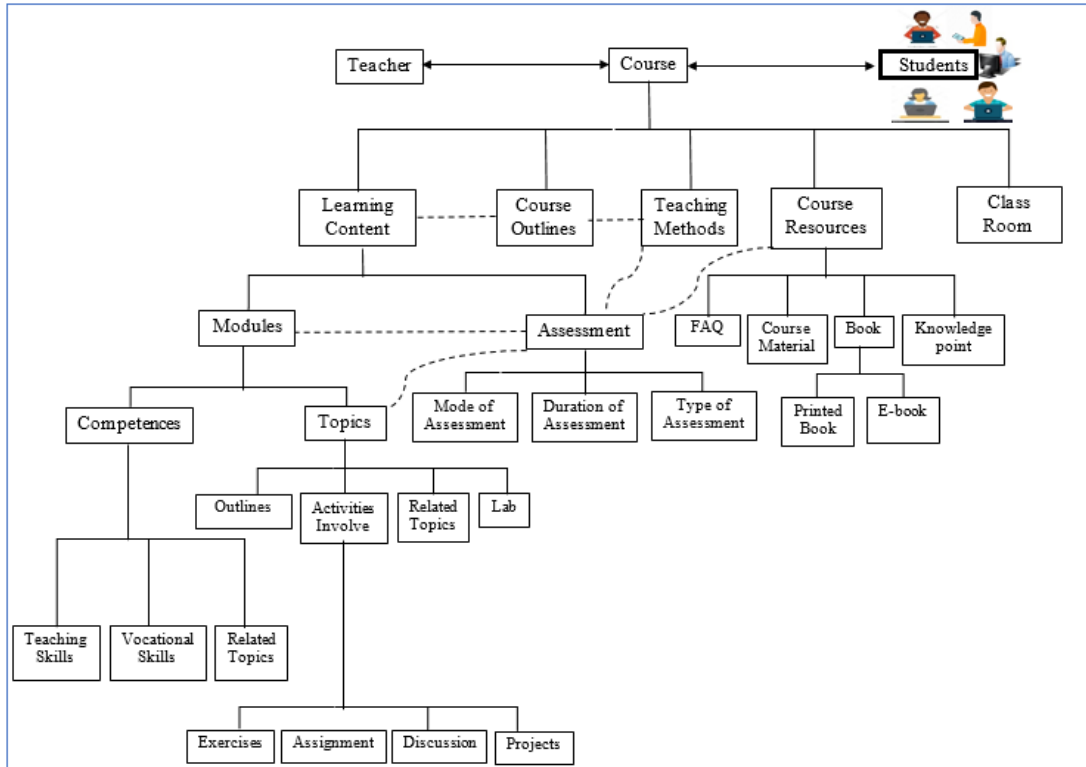


Figure 5 Course ontology model [10]

3.6.2 Ontology-based Domain Knowledge Model for IT Domain in E-tutor Systems

In this research, I have suggested an ontology-based Knowledge domain model for the IT domain in E-tutoring systems. Depending on the properties of the learning materials, two types of ontologies are implemented as a form of general concepts: domain knowledge ontology and specific domain knowledge ontology. These modules represent the knowledge to be learned, deliver input to the expert model, and eventually provide detailed feedback, select problems, generate guidance, and support the student model. The introduced domain knowledge model is constructed based on the current research directions, as shown in Figure 6. The presented model suggests the topics, concepts, attributes, tasks, competencies, assessments, and relations. To facilitate the sharing and reusing of the domain knowledge model features in E-tutoring systems, ontologies are utilized to organize and represent the domain knowledge model. The benefit of this model is to personalize the materials for learners.

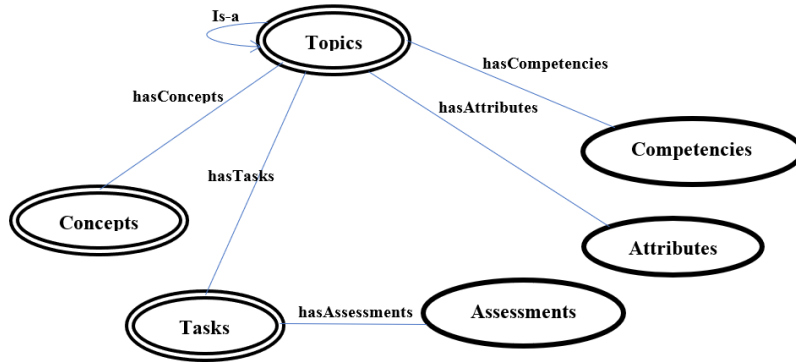


Figure 6 The ontology-based domain knowledge model schema

In the ontology model double line denotes core concepts and single line means core properties. According to the key concepts of the domain knowledge ontology shown in Figure 6. The core components of this model are topics, concepts, attributes, tasks, competencies, and assessment terms refer to the following definitions:

Figure 7 displays the design of a specific domain knowledge case study for the IT domain (computer programming) in an E-tutoring system. I use different types of relationships in the case study, such as specialization or generalization, association, and containment. Containment means that a specific topic within a domain contains different concepts (has-a for example a topic can have a topic part). The specialization or generalization means that certain topics or domains have specific concepts (is-a for example a topic can contain another topic). The association means that a specific topic or concept is associated with another topic.

Based on Figure 6 and Figure 7, the following list shows a brief description of a control structure subject:

- *Topic*: Control Structure.
- *Concept*: Loop, Sequence, and Condition.
- *Competency*: understand, analyze, implement.
- *Task*: program, code review, project
- *Attribute*: syntax, operators
- *Assessment*: activities such as quizzes, tests

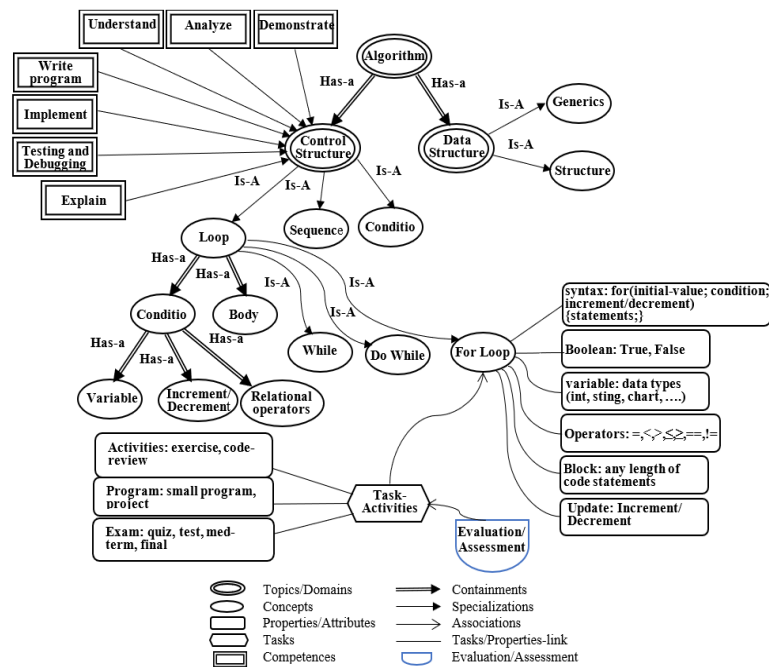


Figure 7 The domain knowledge module for E-tutoring frameworks

3.6.3 Ontology Supported Domain Knowledge Module For E-Tutor Systems

In this research, I suggested an ontology-supported domain knowledge module for an E-tutoring system based on the properties of the learning materials. Two styles of ontologies were introduced: a) general concepts for domain knowledge module ontology and b) specific domain knowledge module ontology. These modules describe the topic to be studied, provide input to the domain module, provide specific feedback, select problems, generate suggestions, and support the learner module. The underlying construction of the suggested domain knowledge module is demonstrated in Figure 8. The model is based on topics, attributes, task assessments, material forms, learning levels, learning rules, and relations. In addition, these model components are designed to support the features of shareability, standardability, flexibility, and reusability for the knowledge domain module. These features can be integrated with the E-tutoring platforms, and I utilized ontology to manage and represent the domain knowledge module. The benefit of this model is to personalize the material forms, make suggestions, and automatic assessments for students.

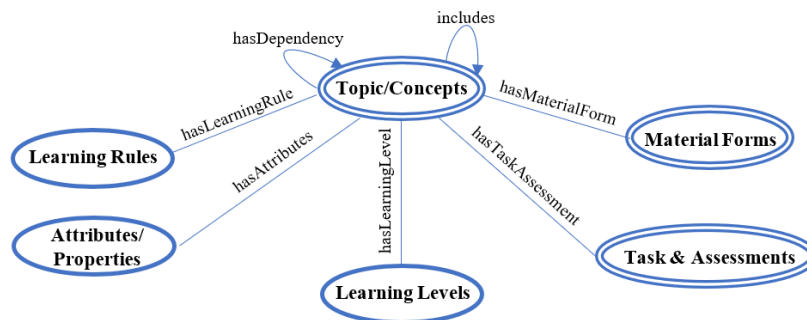


Figure 8 The suggested domain knowledge module

Based on the general concepts of the presented domain knowledge module ontology displayed in Figure 8, the suggested components are: topics, attributes, task assessments, learning levels, learning rules, and material-forms terms refer to the following:

Regarding the primary relationships, the ontology model contains the following elements: Topics taxonomy relationship: it defines the specialization among the topics. Topics component relationship: one topic consists of other topics. Topics-competency relationship across the topics. Figure 9 indicates the case study structure of specific domain knowledge module ontology for the world history domain in the E-tutoring system. Various types of relationships are used in the case study, such as specialization or generalization, association, and containment. Containment denotes that a specific topic within a domain includes different concepts (has-a). The specialization or generalization indicates that the topic has specific topics (is-a). Finally, association means a specific topic associated with attributes/properties, material forms, and task assessments.

Based on Figure 8 and Figure 9, the following list displays a brief description of a World History domain:

- *Topic:* World History, WW I, WW II, Civil War.
- *Dependency:* Battle Name, Factor of War.
- *Task Assessment:* Question/Answer.
- *Attributes:* Events, Durations, locations.
- *Material Form:* Web, Text, Media.

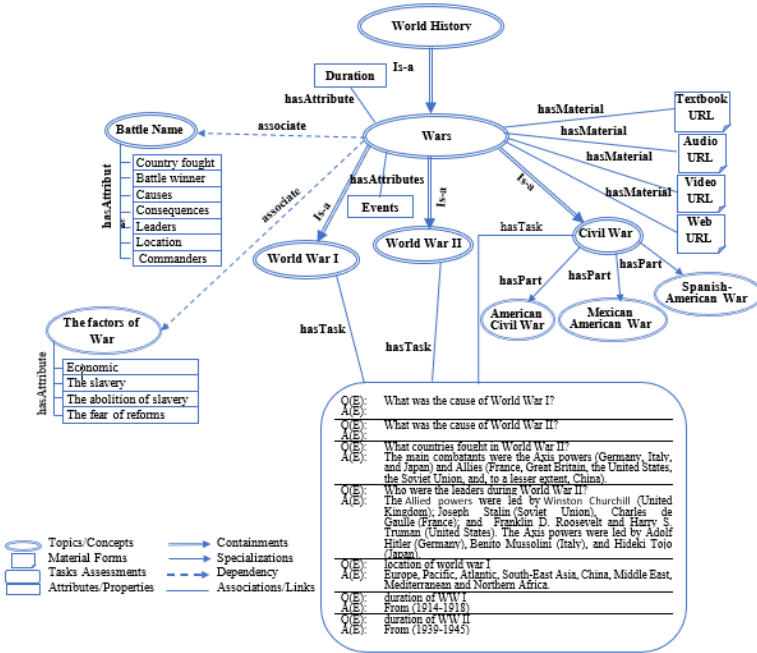


Figure 9 Domain knowledge module sample

3.7 Formal Description of the Domain Knowledge Model

In this section, I introduced the formal definition of the proposed knowledge domain model, which presents the conceptual components of teaching materials frameworks. The domain knowledge model is presented as a coloured graph (or knowledge unit taxonomy) with different node elements and relationships among these nodes. The core concept elements of this model are knowledge units, knowledge slots, task units, rule units, material units, educational units covering the specific teaching and competency dependency units. I also introduce many types of relationships among the knowledge units in the domain ontology. These relationships are specialization or generalization relationships, component relationships, association relationships, and dependency graph relationships.

The domain model Δ is given with a tuple $\Delta (\Sigma, T, \Pi, \Phi, M, \Lambda, \leq, \sqsubseteq, \Rightarrow, \epsilon)$, where:

- Σ : the set of knowledge units (domains, knowledge topics, teaching unit, and key knowledge concepts)
- T : task units (activity, competency related to the knowledge units)
- Π : knowledge slots (property of the knowledge units)
- Φ : rule units (constraints on property values and knowledge units)
- M : material units or teaching materials (textbook, media (video, audio), web)
- L : educational units (learner level)
- Λ : entity type-set (Name, Attributes, on the knowledge units)
- $\leq \sqsubseteq \Sigma \times \Sigma$: generalization, specialization (among the knowledge units)
- $\sqsubseteq \sqsubseteq \Sigma \times (\Sigma \cup \Pi)$: components, the containment relationship on the knowledge units and slots; which means the knowledge unit includes some other knowledge units or slots.
- $\Rightarrow \sqsubseteq \Sigma \times \Sigma$: dependency graph, the competency level dependency on the knowledge units
- $\sim \sqsubseteq \Sigma \times \Sigma$: association (among the knowledge units)

- $\epsilon \subseteq T \times \Sigma$: task – Knowledge-units assignment (activity, assessment on the knowledge unit)

3.8 The Proposed Formal Domain Knowledge Model components

The key structure of our proposed domain knowledge model is shown in Figure 10. The model is based on selected components such as knowledge units, knowledge slots, task units, material units, educational units, rule units and relations. Moreover, to share and reuse the domain knowledge model and integrate it with the E-tutoring systems, ontology is utilized to manage and represent the domain knowledge model. The benefit of this model is to provide personalized learning and teaching, generate material units, make suggestions, and make automatic assessments for students.

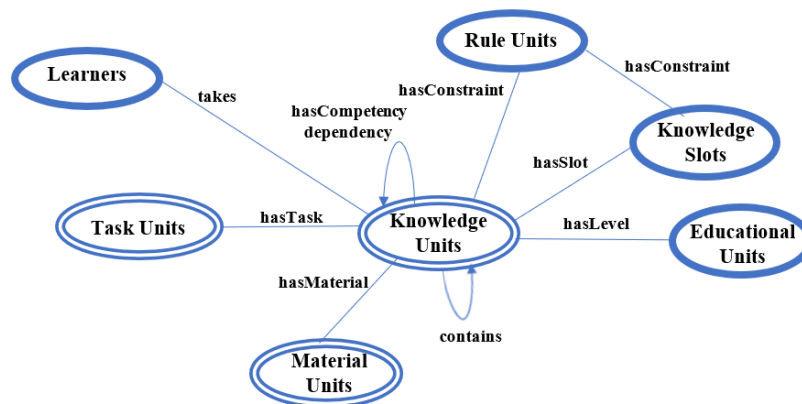


Figure 10 Ontology model schema of teaching materials

In the ontology model double line denotes core concepts and single line means core properties. According to the key concepts of the domain knowledge ontology shown in Figure 10. The core components of this model are knowledge units, knowledge slots, task units, material units, educational units, rule units and their relationship terms refer to the following definitions:

- Knowledge units (K-units) refer to a unit of education and it denoted as domains, knowledge topics, teaching units, key knowledge, and key concepts.
- knowledge slots (K-slots) refer to an atomic property of the k-units. Every slot has a value domain and a value range.
- Task units (T-units) refer to activities related to the k-units and k-slots. T-units can be represented in the form of activities performed by the learners.
- Material units (M-units) refers to teaching materials for the k-units. M-units are teaching materials used to learn the k-units when using the E-tutoring systems.
- Rule units (R-units) refer to rule units as rules or constraints defined on the k-units and the k-slots.
- Educational units (E-units) refer to the level of education that define the learners level when learning different knowledge units, usually at a school, college, or university.
- Generalization is a kind of relationship that indicates one component called a subclass is the basis of another component known as a superclass.
- A component is a relationship, which means one unit consists of other units on the K-units.

- An association describes the relationship between entities or k-units based on shared attributes.
- Dependency is a binary relationship that shows knowledge unit components require or depend on other knowledge unit components for specification or implementation.

4 Assessment module

I developed an assessment module to evaluate the student knowledge level. In this module I used Atanassov's Intuitionistic fuzzy logic technique to manage the uncertain or inaccurate information from the student who takes the task and deals with the uncertainty of the student's knowledge level.

4.1 Knowledge Level Representation

In order to provide personalized training, the E-tutoring system should contain a separate knowledge model for each student. This model covers the training history and the assessment results for every knowledge unit. The knowledge map of the students is in synchrony with the general domain model. Thus, the student's knowledge maps can be considered as an extended version of the domain model. The student knowledge map consists of the following core elements.

- 1) $S = (s_{a1}, s_{a2}, s_{a3}, \dots, s_{am})$: feature vector of the student. It contains, among other the personal data identifiers.
- 2) $KM = (KU, R)$: the knowledge map. Graph of knowledge units (k-units). Every k-unit in KU has a corresponding item in the domain model. The component R denotes the set of relationships among the k-units, including the specialization relationship or the containment relationship or the competency dependency relationship.
- 3) A_L : the set of knowledge-level attributes of the KU units. The main attributes are as follows.
 - a) Measured knowledge level value (A_{LM}) at the k-unit.
 - b) Expected knowledge level value (A_{LE}) at the k-unit.
 - c) History of learning activities (A_H) related to the k-unit.
 - d) History of related assessments (A_A)

Regarding the knowledge level value attribute, we use an intuitionistic logic value to denote the knowledge and the competency level. The primary motivation for selecting this representation mode is that this formalism is able to present the uncertainty level. Thus, we are able to use three aspects in the description:

- Perfect competency
- No competency
- We have no information about the competency.

According to the formalism of intuitionistic logic, $A_L = (l_T, l_F)$, where:

l_T : the level of perfect competency $0 \leq l_T \leq 1$

l_F : the level of no competency $0 \leq l_F \leq 1$ and $l_T + l_F \leq 1$

Initially the A_L values are set to $(0, 0)$ as we have no information about the knowledge level of the student.

The main difference between the expected and measured knowledge levels is that the measured value is based on the concrete assessment results of the student. As the assessments usually cover only a fraction of the related knowledge units, the ratio of unknown values is relatively high. The other component, the expected competency level, is based on the processing of the measured competency levels of other students, using a machine learning approach for value prediction.

4.2 Calculation of the competency levels

The context of the calculation of the expected competency value can be given with a competency matrix CM , where the notation of the columns:

A_1, \dots, A_m : attributes. Every attribute corresponds to a value range of measured competency (or feature value component in the student description).

C_1, \dots, C_v : value categories of the expectation value at the target knowledge unit. The values in the cells are True (1) or False (0) values, depending on whether the attribute is valid at the given object (row) or not. The following table (Table 2) displays the expected competency level value related to the knowledge unit.

Table 2 The expected competency level

| A_1 | A_2 | A_3 | A_4 | C_1 | C_2 |
|-------|-------|-------|-------|-------|-------|
| 1 | 0 | 0 | 1 | 1 | 0 |
| 1 | 1 | 0 | 0 | 0 | 1 |

For the prediction of the expected value for a given (student, knowledge unit (k-unit)) pair, we use the Bayes classifier. The Bayes classifier output is the category with the highest score which is calculated from the corresponding conditional probabilities.

$$C_w = \operatorname{argmax}_c \left\{ P(c) \prod_a P(a/c) \right\} \quad (7)$$

The expected value shows that the k-unit with higher score value can be suggested to the student as a new k-unit for learning.

The measured competency values are changed after every assessment unit. In the selection of the k-unit for the assessment, we should take those k-units, which help to discover the unknown areas in the competency map.

The algorithm to select a knowledge unit:

1. Suppose there are k-units with uncertainty or with low-level value. In that case, we should choose one of these k-units where this value is equal to the product of the uncertainty level of the measured level and the inverse of the adjusted expected competency level. We order a selection probability for each task unit (the higher the relevance value, the higher value has the chance of selection).
2. The student performs the assigned task, and we get the result.
3. We evaluate the response and get an accuracy level for each k-units related to this task.
4. We update the knowledge map of the student.
5. We give more suggestions to the student on which parts and study aids should he/she learn and practice.

If the current value is (l_T, l_F) for the k-unit, and the score of the solution is g (g is normalized in $[0,1]$) and the relevance of the k-unit in the task was r (r in $[0,1]$), then.

$$l_T = \frac{(n * l_T + g * r)}{(n + 1)} \quad (8)$$

$$l_F = \frac{(n * l_F + (1 - g) * r)}{(n + 1)} \quad (9)$$

Where n is the number of previous updates.

The assessment process in the prototype system is an interaction cycle between a student and the system. This process contains a student login to his knowledge model, a random selection of a knowledge unit, a task, a related question, a student answer, an evaluation, and a student knowledge model update.

I have used MCQ tasks related to the knowledge unit to check the student's knowledge level after every knowledge unit concept. After the student correctly answers the MCQ tasks related to the knowledge unit concept, it means that the student learned this knowledge unit so that the system will update the student's knowledge level accordingly. If the student's answer is not correct or not satisfactory, the level values of the knowledge unit are not updated. According to the update on student knowledge level, the E-tutoring system can generate a new task and provide personalized teaching and learning materials through a student model based on task scores on domain knowledge unit concepts. The E-tutoring system also offers suggestions. The suggestion related to task question, the student result, knowledge level progress, and suggest reading materials.

5 Model Storage Systems for the Ontology Model

In my research, I investigate and compare three main different ontology storage methods from the viewpoint of adaptivity to the E-tutoring framework. The three models are ontology OWL, Jena Fuseki, and the relational model. I tested and evaluated the selected model storage systems by conducting an experiment applying ten test queries. The test result shows that Jena Fuseki and the relational model are the best model storage systems compared with the ontology OWL file. The suggested module can be improved by adding some functionalities and automatically supporting the generation of problems and their solutions.

5.1 Implementation and Test of the selected model storage systems

The domain knowledge model is implemented in three ways: ontology OWL file structure, relational data model, and Jena Fuseki model storage systems. The goal is to determine whether each of these models is better when evaluating them by selecting the execution time criteria. Many relationships are used in the selected case study, such as specialization or generalization, association, competency dependency, and containment. Containment means that a specific knowledge unit within a domain contains different knowledge units (hasPart). Specialization or generalization means that certain knowledge units have specific knowledge units (is-a). The association means that a specific knowledge unit is associated with another knowledge unit. Competency dependency means specific knowledge units can have a competency dependency with other knowledge units.

Different styles of test queries are executed for testing and evaluating the performance of the selected model storage systems ranging from a very simple query, normal query, advanced simple query, intermediate query, upper intermediate query, and advanced intermediate query to a very complex query. The simple query refers to the problem that only needs to query atomic triple data with a relationship to get the answer. The query example for the very simple is "List all the knowledge units?". The intermediate query refers to the problem that needs to query for more than atomic triples data with one or two relationships to get the results. For example, the intermediate query is "What are the task units of each knowledge unit?". The upper intermediate query in the example is "Find all task units, related questions, and material units of the knowledge units?". The complex query refers to the problem that requires querying for more than atomic triples data with many relationships to get the results. The complex query in an example is "Find all task units, related questions, material units, and educational units of the knowledge units?". The levels of test queries cover the computer programming course.

5.2 Test Result

The selected model storage systems are tested by conducting an experiment applied to a small and large database concerning ten test queries. Each test query is executed ten times, measuring the execution time for every test query. The result of this experiment was described in Tables 3 and 4, which show the execution time average for each test query for the three models applying for the small and large amounts of data.

Table 3 Test query performance for small database

| Query Execution Time | Jena Fuseki | OWL file | Relational Model |
|----------------------|-------------|----------|------------------|
| Query Test 1 | 0.020 | 0.205 | 0.021 |
| Query Test 2 | 0.024 | 0.220 | 0.028 |
| Query Test 3 | 0.029 | 0.253 | 0.028 |
| Query Test 4 | 0.031 | 0.218 | 0.030 |
| Query Test 5 | 0.027 | 0.256 | 0.030 |
| Query Test 6 | 0.029 | 0.210 | 0.030 |
| Query Test 7 | 0.033 | 0.211 | 0.031 |
| Query Test 8 | 0.032 | 0.250 | 0.031 |
| Query Test 9 | 0.026 | 0.253 | 0.029 |
| Query Test 10 | 0.037 | 0.257 | 0.028 |

Table 4 Test query performance for large database

| Query Execution Time | Jena Fuseki | OWL file | Relational Model |
|----------------------|-------------|----------|------------------|
| Query Test 1 | 0.024 | 0.361 | 0.022 |
| Query Test 2 | 0.030 | 0.406 | 0.031 |
| Query Test 3 | 0.033 | 0.357 | 0.031 |
| Query Test 4 | 0.031 | 0.392 | 0.030 |
| Query Test 5 | 0.043 | 0.354 | 0.034 |
| Query Test 6 | 0.039 | 0.408 | 0.033 |
| Query Test 7 | 0.039 | 0.374 | 0.030 |
| Query Test 8 | 0.034 | 0.379 | 0.030 |
| Query Test 9 | 0.032 | 0.373 | 0.031 |
| Query Test 10 | 0.035 | 0.443 | 0.031 |

Comparing the execution time between Tables 3 and 4 linking the value of some test query related to the small and large database are given in the following explanations.

In Table 3, the query test 1 for the ontology OWL file model takes 0.205 seconds, while Jena Fuseki model takes 0.020 seconds, and the relational data model takes 0.021 seconds. For query test 7, ontology OWL file model takes 0.211 seconds, while Jena Fuseki model takes 0.033 seconds and relational data model takes 0.031 seconds. For other select query test 8, ontology OWL file model takes 0.250 seconds, Jena Fuseki model takes 0.032 seconds, and relational data model takes 0.031 seconds. While in Table 4, a query test 2 for the ontology OWL file takes 0.406 seconds, while Jena Fuseki takes 0.030 seconds, and the relational data model takes 0.031 seconds. For query test 7, the ontology OWL file model takes 0.374 seconds, while Jena Fuseki model takes 0.039 seconds and relational data model takes 0.030 seconds. For other select query test 9, ontology OWL file model takes 0.373 seconds, Jena Fuseki model takes 0.032 seconds, and relational data model takes 0.031 seconds.

As a result, the investigation showed that Jena Fuseki and relational data model have a minimum execution time which means that Jena Fuseki and relational data model are the best model storage systems compared with ontology OWL file, as shown in Figures 11 and 12. explain the query test result according to the execution time of the three models.

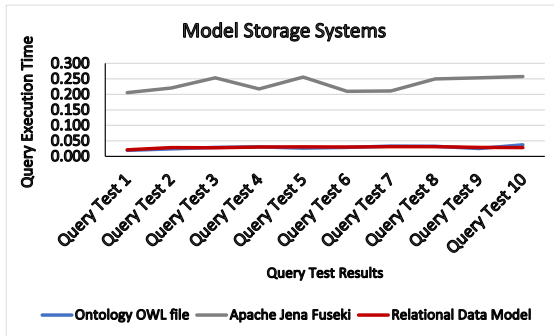


Figure 11 Test query performance for small database

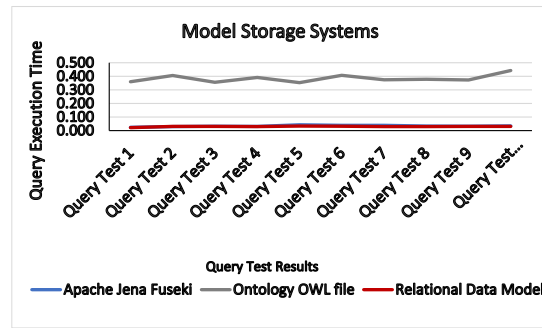


Figure 12 Test query performance for large database

6 Functionality of the Prototype System

I developed a prototype framework and added functionality by implementing and integrating the knowledge domain model for an E-tutoring framework. Regarding the domain knowledge model implementation for an E-tutoring system and the ontology as a back end. The prototype system and the ontology model are implemented using the Python Flask framework and OWLReady2. Several task assessments were performed to evaluate the prototype system integrated with the ontology domain knowledge module and the functional test. According to that, the result gives correct feedback according to the student's answer showing if the answer is correct or incorrect and offering suggestions. The suggestion related to unit name, task name, task question, learner answer, the result, suggested reading material, and the task level score.

6.1 Case Study in the Domain of Teaching Programming

The ontology domain refers to an area in teaching programming at introduction level. The selected domain relates to a specific programming language, namely C++. This domain is an essential topic for most students studying in many disciplines, such as education, engineering, and mathematics. The domain knowledge model covered in this example case study is the loop structures in a programming language. The main goal is to help the students to understand and practice the loop structures in computer programming. This example case study is based on the selected ontology model of the domain knowledge model that presents the conceptual components of teaching materials and their relationships.

In order to measure what the students understand and learn, it is not sufficient to evaluate their knowledge level and skills at the final step of the study program. It is also important to discover the students' present knowledge level of a domain, so that we can determine more specifically the knowledge level and skills they have acquired during the study program. In this case, we need a technique to describe the operations for testing and evaluating the student's knowledge level.

In the prototype system, a knowledge model is separated for every student. This knowledge model is constructed based on the domain knowledge model. It stores a knowledge level for each knowledge unit. The level value should consider that, in most cases, we have no information about the competency level for all knowledge units. Thus, we should manage the case of missing information. In order to denote the uncertainty information, an Intuitionistic logic value is used with the level value of true and the level value of false. The following steps define the operations of evaluating the student knowledge level:

- Initially, for every knowledge level, I set $(0, 0)$ for the level value.
- First, the system will check if there are knowledge units (k-units) with uncertainty or low value. In that case, the system should choose one of these k-units where this value is equal to the product of the uncertainty level of the measured level and the inverse of the adjusted expected competency level. We order a selection probability for each task unit (the higher the relevance value, the higher value has the chance of selection).
- The student performs the assigned task, and we get the result.
- We evaluate the response and get an accuracy level for each k-units related to this task.
- We update the knowledge map of the student.
- We give more suggestions to the student on which parts and study aids should he/she learn and practice.

6.2 Loop Structures Knowledge Units Case Study

Loops in programming are the knowledge units case study covered in this research. Loops in programming language allow us to repeat one or more expressions many times as required. Loops are instructions that repeat until a particular condition is satisfied. Typically, in a particular operation, such as obtaining and updating data, conditions are verified, such as whether a counter has reached a specific counter. Loops are part of control structures which

include For, While, and Do-While loops. In Figure 13, I consider the loop structures as a knowledge unit use case.

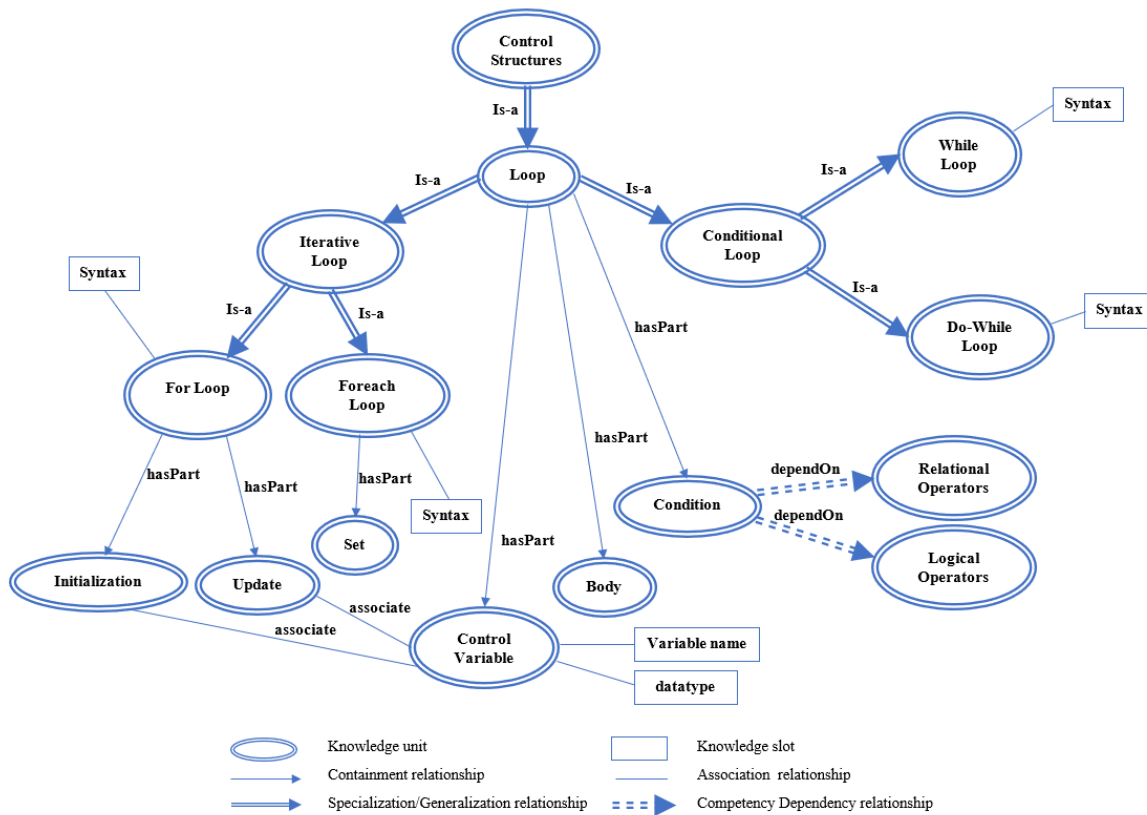


Figure 13 The specific domain knowledge module of teaching materials

6.3 Testing and evaluation

Testing is a process of checking the design and functionality of the prototype system or components that meet the requirements and specifications via applying testing techniques in the software engineering domain [11]. The developer or the learners can evaluate the outcomes to assess the improvement of the design, performance, supportability, etc. The development of testing is an engineering mechanism used to reduce the risks during the software design process. Operational testing is the actual or simulated application, by specific users, of a system under practical, functional conditions [11].

A functional test was done to evaluate the student knowledge level in the prototype system, which is integrated with the ontology domain knowledge model. Several task assessments with MCQ were performed. According to that, the result gives feedback according to the student's answer showing if the answer is correct or incorrect. The system will update the student status according to his/her task assessment solution and the offer suggestions. The suggestion is related to task questions, student correct and wrong answers, the student result, knowledge level progress, and suggested reading materials.

Figures 14 and 15 display a test evaluation of the task assessments for different practices that allow the student to answer the task questions related to the knowledge unit, and then the student chooses the correct answer and moves to the next task question. After that, the prototype system

checks whether the answer is correct or not and provides feedback according to the student's answer.

Welcome, ...

Task Activity Practice

Question 1 of 6

In the codes shown, will the statement "Hello!" be displayed?

```
counter = 0;
do {
  cout << "Hello!";
}while(counter > 0);
```

A. Yes, once
 B. No
 C. Yes, forever (infinite loop)
 D. Yes, twice

Next

Figure 14 Snippets of practice task assessment

Programming E-Tutoring

Home Dashboard About Feedback Contact Profile Logout

The Results!

| Number of Correct answers | Number of Wrong answers | Student Result | Level of True | Level of False | Recommended Materials |
|---------------------------|-------------------------|----------------|---------------|----------------|--|
| [1, 2, 3, 5, 6] | [4] | 0.83 | 0.45 | 0.1 | To master your learning you should read more about the Knowledge units in the following materials, C++ for Loop: https://www.programiz.com/cpp-programming/for-loop Control Structures II Repetition: https://slideplayer.com/slide/5025236/ C++ Programming From Problem Analysis to Program Design: C++ Programming from Problem Analysis to Program Design-Cengage Learning |

you are doing Great Job

Figure 15 Snippets of the task assessment result

7 Thesis Summary

The following four dissertation thesis summarize the novel scientific research results of an experience achieved during my thesis work:

Thesis 1: I have developed an adaptive E-tutoring system architecture. Beyond the standard components, this architecture also includes a common shared database and knowledge-based background. The main benefits of this architecture are that it supports shared databases providing more features. The features are efficient knowledge management, flexibility, better performance, scalability, increased accessibility and availability, better security, and automatic recovery. They also provide the required technical and methodological background for developing smart tutoring systems. Besides this adaptive architecture, I have developed and tested three model versions of the domain knowledge module based on ontology methods in order to create a general and flexible model and enhance the learning processes. The proposed model can improve the semantic support of the related decision-making processes. The main role is to support the automatic control of teaching processes and automatically selecting assessment material from a predefined pool according to the student's capabilities. The proposed model is presented as a model structure containing two types of ontology models, general concepts of domain knowledge ontology and specific domain knowledge ontology. The expected benefits are to enhance the learning and teaching process, provide support for recommendations, generate hints, automatically support the generation of problems and solutions, and automatically support the generation of teaching materials. [2] [3] [4] [8]

Thesis 2: I have introduced a novel formal logical ontology domain knowledge model for an E-tutoring system, which presents the conceptual components of teaching material frameworks. The core components of this model are knowledge units and related units covering the specific teaching and competency dependency units, including the specialization, containment, association, and dependency graph relationships among the knowledge units in the ontology domain. For storing this model, I compared three model storage systems the OWL ontology file, Jena Fuseki, and the relational model. The key aspect is determining the suitable storage model to store the ontology model in a standard, efficient, scalable, and consistent format. The main role of this comparison is to improve application performance, enable semantic knowledge representation, and achieve efficient information retrieval. The investigation shows that Jena Fuseki and the relational model are the best ontology storage tools. They provide support facilities for storing, inferring new knowledge, and managing the ontology domain knowledge. [4]

Thesis 3: I have presented a knowledge model to manage the students' competency levels and to support automatic decision-making in the smart tutoring framework. The

proposed knowledge model supports the representation of uncertainty in students' knowledge and can be used to identify their status in the learning processes. In the assessment module, I used intuitionistic fuzzy logic values to represent the uncertainty in student knowledge status. The intuitionistic fuzzy logic values can be used to automatically identify the status of the students' knowledge level. I have developed an algorithm for the evaluation of the student's performance using an accumulative task assessment approach with multiple-choice questions. The model automatically updates the student's knowledge level in an adaptive way. The proposed model provides interactive and adaptive assistance techniques by personalizing the teaching and learning materials according to the current knowledge levels. [5]

Thesis 4: I have developed a prototype software system based on the proposed E-tutoring framework integrated with the ontology domain knowledge model. The framework implements the presented decision support algorithms for personalized E-tutoring. The prototype E-tutoring system can enhance the quality and functionality of intelligent e-learning systems. The performed experiments and tests with the prototype framework show that flexible functionality and personalization of the learning materials, automatically generating new task assessments, and providing hints and recommendations to the student, can significantly improve the efficiency of the e-learning systems and can enhance the functionalities of teaching and learning processes. [3] [5]

Author's Publications

Publications Related to the Dissertation

Journal Articles in Q Ranking

- [1]. **Ghanim Hussein Ali Ahmed and László Kovács**, Development of Ontology-based Model to Support Learning Process in LMS, *INDONESIAN JOURNAL OF ELECTRICAL ENGINEERING AND COMPUTER SCIENCE* 24(1), pp. 507-518, (2021) **Scopus (Q3), Impact Factor (1.51)**, Journal Article.
- [2]. **Ghanim Hussein Ali Ahmed, Jawad Alshboul and László Kovács**, Development of Ontology-based Domain Knowledge Model for IT Domain in E-tutor Systems, *INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS (2158-107X 2156-5570)*: 13(5), pp. 28-34, (2022), **Web of Science (WoS), Scopus (Q3), Impact Factor(1.16)**, Journal Article.
- [3]. **Ghanim Hussein Ali Ahmed and László Kovács**, Ontology Supported Domain Knowledge Module For E-Tutoring System (accepted with minor revision), *Acta Cybernetica*, **Scopus (Q3), Impact Factor(0.64)**, Journal Article.
- [4]. **Ghanim Hussein Ali Ahmed and László Kovács**, Model Storage Systems for Integrating the Ontology Domain Knowledge Module in E-Tutoring Systems (submitted, in review process), *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, **Scopus (Q3), Impact Factor(1.5)** Journal Article.
- [5]. **Ghanim Hussein Ali Ahmed and László Kovács**, Assessment Module for Evaluating Student Knowledge level in E-tutoring Systems Using Intuitionistic Fuzzy Sets Technique (under progress), expected to be published in **Scopus (Q2) journal**.

Other Publications Journal Articles in non-Q Ranking

Local Journals

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International Journal

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International Conference Proceeding

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Book of Abstract

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