Models of knowledge representation applied in higher education

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Abstract: *A proper integration of knowledge in computer-based educational resources is essential for the efficiency of course teaching and student learning. In order to maintain the knowledge meaning in educational processes that are intermediated by computers it is necessary to choose a suitable way of representing knowledge. The paper presents an overview of knowledge representation models that are or can be applied in higher education. Also, it is presented a case study of representing knowledge for the course of Artificial Intelligence teached to Computer Science undergraduate students at Petroleum-Gas University of Ploiesti. The models that are discussed in the example are ontologies, knowledge graphs and procedural models. A synthesis of current trends in representing higher education knowledge is also included in the paper.*

Keywords: Knowledge representation model, Higher education, Ontologies, Knowledge graphs.

1. Introduction

Knowledge is the most important resource that is shared in educational processes. Each course that is teached to specific higher education specialization has its knowledge derived from books, textbooks, research articles, tutorials, other educational materials, and professor' experience. Also, each course has prerequisite knowledge that usually refer to courses that were studied by students in previous semesters or it refer to basic knowledge teached in school. Computer-based education requires efficient methods for representing knowledge so that it is kept the meaning and the teaching and learning processes are facilitated. There are several types of knowledge representation models starting from symbolic logic, procedural methods, structural methods and ending with large language models that started to be applied in education. An introduction on the subject of knowledge representation in artificial intelligence-based systems is presented in the textbook (Russell & Norvig, 2020). The models that are currently applied to knowledge representation are specific to artificial intelligence (AI) and linguistic.

The paper presents an overview on knowledge representation models focusing on those that were or can be applied in higher education. A case study of using knowledge representation models for the course of Artificial Intelligence

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teached to Computer Science undergraduate students at Petroleum-Gas University of Ploiesti is discussed in detail. Finally, the current trends in representing higher education knowledge are highlighted.

2. Knowledge representation models

The main types of knowledge representation models (Russell & Norvig, 2020) are symbolic logic, procedural models, and structural models. Symbolic logic includes, usually, first order predicates logic and production rules. Procedural models refer to procedures and functions that represent knowledge. Structural models describe knowledge primarily as a structure with components and relations between them or as a detailed sequence of events that take place in a certain context. If uncertainty has to be included in knowledge representation there are several methods that can be used, as for example, fuzzy logic, uncertainty coefficients, probabilistic methods, and Bayesian Networks. These methods can be integrated in the knowledge representation models. An extensive analysis of various knowledge representation methods is given in the handbook (van Harmelen et al., 2008).

2.1 A taxonomy of knowledge representation models

The knowledge representation models can be classified in a hierarchy as shown in Figure 1. We have included some knowledge uncertainty representation models.

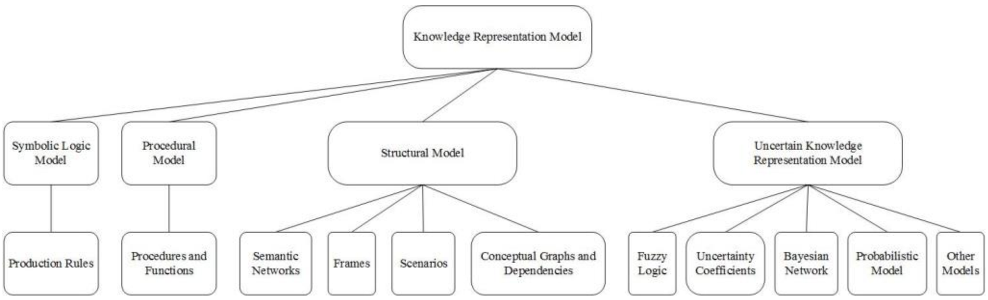


Figure 1. A classification of knowledge representation models

The symbolic logic model facilitates the representation of knowledge components and the relations between them usually, in terms of first order predicates or production rules, when it is a decision type knowledge that either derive new knowledge or executes a specific action.

A procedural model specifies step by step the instructions/actions that should be performed in sequence when knowledge is applied to solve a problem.

A structural model describes the structure of knowledge, its components and the relations between them either as a graph/network or as a prototyped form with slots and a specific program (a set of events). Examples of structural models, as they were reported in the literature, are: semantic networks (Quillian, 1967), frames

(Minsky, 1975), scenarios (Schank & Abelson, 1977), conceptual graphs (conceptual maps) and conceptual dependencies (Sowa, 2008). Most of the structural models are based on linguistic models. There are also models for representing uncertain knowledge such as fuzzy logic (Zadeh, 1965), uncertainty coefficients, Bayesian networks (Pearl, 1988), probabilistic models and other models (Russell & Norvig, 2020).

A semantic network is a graph with nodes representing concepts and arcs representing relations between concepts. The term of knowledge graphs was introduced in 2012 by Google and is similar to semantic networks. A frame is a model for representing a stereotype system with slots and facets. A scenario describes a sequence of events taking place in a specific context. Conceptual graphs and conceptual dependencies are linguistic models and they can be viewed as knowledge graphs (Serles & Fensel, 2024). Other models of knowledge representation include ontologies that conceptualize a specific domain of expertise (Staab & Studer, 2009) and large language models (Vaswani et al., 2017) specific to generative AI that use deep learning and the transformer architecture and are trained on massive text datasets generating answers to users in text format. A large language model (LLM) is a type of natural language processing model for writing and conversation.

In the next section it is presented a survey on knowledge representation models focusing on those that were applied in higher education or have the potential to be used in education. The articles were published in the period 2019-2026.

2.2 A survey of knowledge representation models for higher education

Several overviews on knowledge representation were presented in the literature in the last decade. A systematic review of the research work published in the period 1980-2017 with topics related to knowledge representation in educational environments is presented in (Buitrago & Chiappe, 2019). The authors selected 200 papers from three databases (Web of Science, Scopus and Scielo) and read in-depth 100 papers. One of the main conclusions was that the models that were most used for representing knowledge in educational environments are conceptual maps. Several types of educational activities were analysed as for example, learning assessment, problem solving, decision making, and learning styles analysis. Another literature review on the application of knowledge graphs in education is synthesized in (Rizun, 2019).

A case study of knowledge graphs use for databases course teaching activity is described in (Qin et al., 2020). Thus, a systematic teaching content was created with knowledge graphs, enabling an improvement of student learning quality.

The theory and practice of knowledge graphs focusing on recent trends is discussed in (Tiwari et al., 2021). Three types of knowledge graphs were analysed, general purpose KGs, expert KGs, and industrial KGs. In this research, a knowledge graph is a knowledge base represented in the graph. The main types of

KGs applications are: knowledge sharing, knowledge management, recommender system, knowledge management, dashboard, question-answering, dashboard and knowledge sharing.

An analysis of learners' knowledge representation modelled as cognitive networks is reported in (Siew, 2022). By using learning analytics on data related to educational practice of student's new knowledge is derived for adaptive learning.

An example of applying knowledge graphs in higher education of art and design is given in (Fan et al., 2024). The research work focused on applying knowledge graphs for curriculum design, student learning (providing personalized learning paths), teaching activity (providing innovative teaching methods), and assessment activity (including multi-dimensional assessment). The study revealed an improvement of students' abilities facilitated by knowledge graphs use.

A knowledge graph-based model for personalized educational and career recommendations simplifying the adaptation of university educational programs to the requirements of employers is introduced in (Ramazanova et al., 2024). The knowledge graphs are used to aggregate and analyse a variety of data related to university courses, skills, and job vacancies. Multilingual semantic similarity algorithms were applied for matching skills in educational programs and specific courses with skills necessary for job vacancies.

A methodology for educational knowledge graphs construction assisted by AI is presented in (Aytekin & Saygin, 2024). The ACE methodology combines machine learning (ML) techniques with expert knowledge and provides paths that students can follow in the learning activity.

An application of knowledge graphs and LLMs for the identification of core concepts included in educational resources is described in (Reales et al., 2024). The authors provided three solutions that build knowledge graphs from lecture transcripts by using LLMs and ontologies.

A new approach for representing curriculum in higher education is presented in (Piriyapongpipat et al., 2024). In order to provide a flexible and responsive curriculum, the authors proposed the extraction of basic knowledge (such as skills) from external source data into an ontology. Examples of using the proposed approach for courses in Computer Science domain are given.

A systematic review on LLMs use in smart education is reported in (Xu et al., 2024). The research work focuses on current technologies, challenges and future developments for personalized assessment in a smart educational environment.

A recent survey on using large language models in knowledge representation learning is presented in (Wang et al., 2025a) emphasizing the improvement of student learning ability.

A combination of three knowledge representation models, LLM, knowledge graphs and ontologies are discussed in (Kim et al., 2025). The authors introduced KONDA, a tool based on LLM for semantic annotation and creation of knowledge graphs with ontologies that was applied to research data.

Another research work that applied knowledge graphs to interdisciplinary higher education is presented (Wang et al., 2025b). Basicaly, interdisciplinary tools were developed for the construction of interdisciplinary knowledge graphs used for student learning in engineering management.

An example of using LLMs as teacher' assistants for teaching plans preparation is given in (Hu et al., 2025). A simulation of teacher-student interaction is presented, for the High School of Mathematics. LLMs were chosen for the enhancement of teaching plans quality.

A semantic model, an ontology, SmartLearningOnto, modelling various aspects of a smart learning environment in a smart campus is proposed in (Nagowah et al., 2025). The main goal of this ontology is to provide semantic interoperability facilitating data exchange between the systems included in an IoT-enabled smart campus as e.g. e-learning, smart library, smart classroom. Moreover, the ontology infers new knowledge that improve the student learning experience.

Another recent systematic review on LLMs use in educational environments (e.g. in Intelligent Tutoring Systems) is reported in (Shi et al., 2026). The period that was analysed is November 2022 - March 2025. The review revealed that most of the studies were performed in Asia, commonly for the domain of Computer and Technology.

The survey that was performed on articles published in the period 2019-2026 showed that knowledge graphs are most used knowledge representation model. Ontologies are also used in education and the current trends are related to the integration of LLMs and explainable AI. An example is given by a framework XAI-ED that includes explainable AI in education and is described in (Khosravi et al., 2022). A final remark is that conceptual graphs/maps, and semantic networks are basically knowledge graphs, being usually considered as synonym terms.

3. Case study

As a case study it is considered the discipline Artificial Intelligence that is teached at Petroleum-Gas University of Ploiesti to undergraduate students from the Computer Science specialization in the fourth year of study that has as educational activities, course teaching, laboratory and project. We have designed and implemented in Protégé (https://protege.stanford.edu) an OWL ontology named Onto-AI for Artificial Intelligence course teaching and student learning starting from the learning objectives that were established at the beginning of discipline planning.

The use of knowledge representation models for the following types of activities were analysed: discipline planning, course teaching and student learning.

3.1 Discipline planning

When planning the subjects covered by the Artificial Intelligence discipline several issues must be considering, as for example, the learning objectives, the prerequisite knowledge, the order of course subjects and their synchronization with the laboratory activity and the project activity. Figure 2 shows a general knowledge graph related to AI discipline planning.

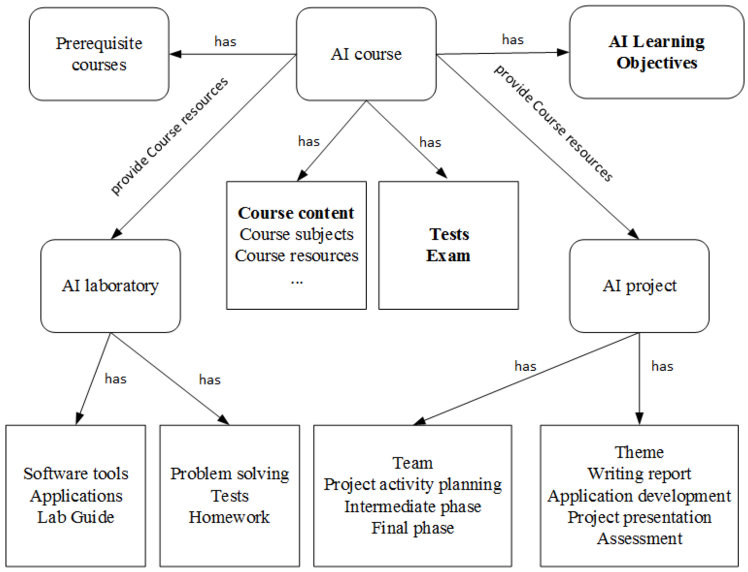


Figure 2. A general knowledge graph for AI discipline planning

Figure 3 presents the list of prerequisite courses as well as the main subjects covered by AI course and a list of general themes for AI project.

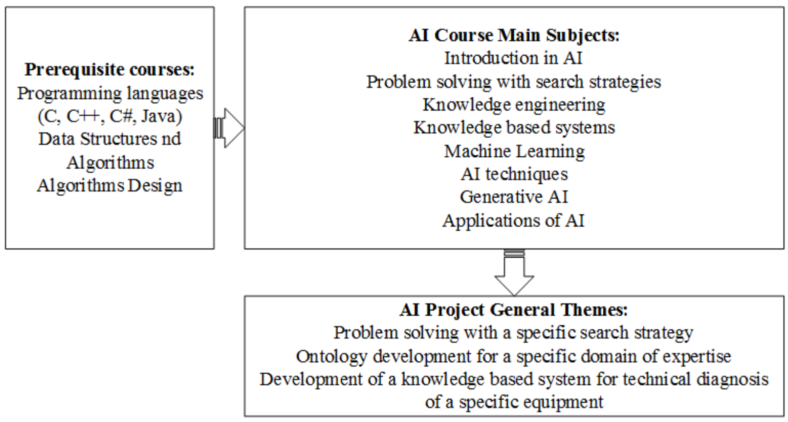


Figure 3. List of prerequisite courses, AI course subjects and the list of general themes for AI project

As the AI project has two phases, an intermediate one that refers to the design of the solution adopted for the project theme (i.e. solution design), and the final one that refers to the solution implementation and project report writing, the planning of the course main subjects that are necessary for the AI project was made so that the theory is teached before finalizing the intermediate phase.

3.2 Course teaching and student learning

A conceptualization of the AI course subjects was made under the form of an OWL ontology, Onto-AI, implemented in Protégé. The main concepts (implemented as classes in Protégé) were identified and defined for each course subject according to the AI course learning objectives. Next, the attributes and characteristics that are needed were defined as DataProperties and the relations between concepts were defined as ObjectProperties. Figure 4 shows a part of concepts hierarchy and Figure 5 shows a selection of DataProperties and ObjectProperties.

Figure 4. Onto-AI ontology concepts hierarchy in Protégé (selected classes)

We have included in the Onto-AI ontology some basic concepts that are needed by specific AI course subjects, as for example, the concepts of **State**, **Node**, **Solution**, **Search_Space** that are necessary for the subject of *Problem solving with search strategies*.

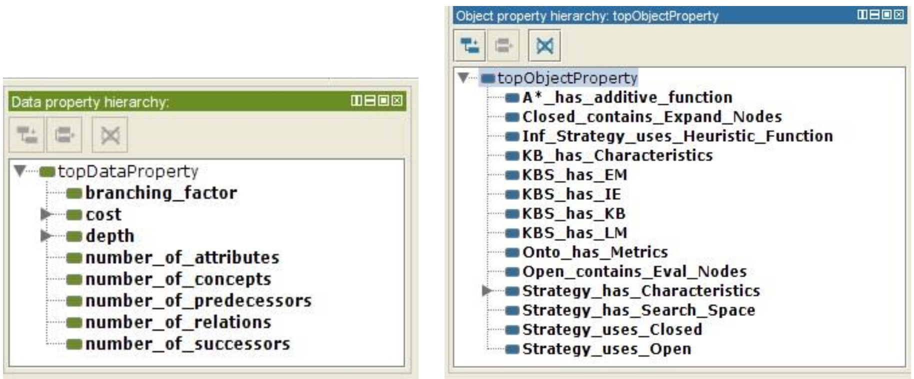
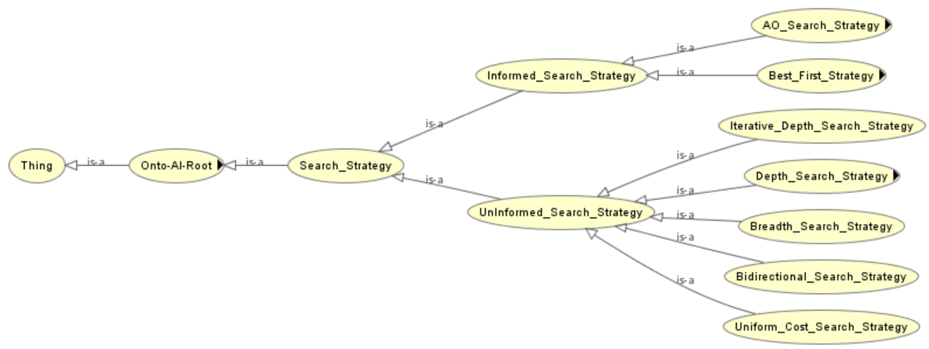


Figure 5. Onto-AI ontology selected DataProperties and ObjectProperties in Protégé

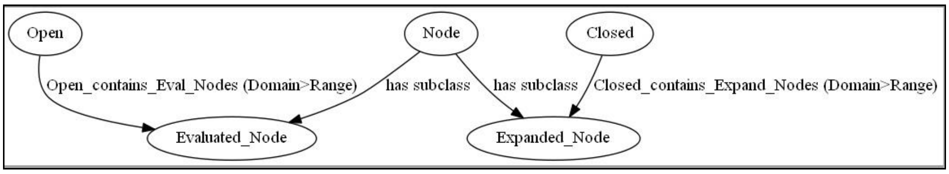
Examples of attributes that were needed for the definition of concepts from the *Problem solving with search strategies* subject are **branching_factor** for the **Search_Space**, **depth** and **cost** for the problem solution.

The knowledge provided by the Onto-AI ontology can be visualized as knowledge graphs with different visualization tools (e.g. OWL Viz for taxonomies, OntoGraph or GraphViz). These knowledge graphs are used for course teaching and for student learning with the goal of improving the educational processes related to the Artificial Intelligence discipline. Examples of taxonomies and knowledge graphs are given as follows.

Some basic knowledge resources that are used for teaching and learning the subject of *Problem solving with search strategies* are given in Figure 6. We have included a taxonomy for search strategies and a knowledge graph for the definition of Open and Closed lists that are used by the algorithm of the search strategy. A procedural model is used to represent the search strategy' algorithm (e.g. the A* algorithm).



(a)

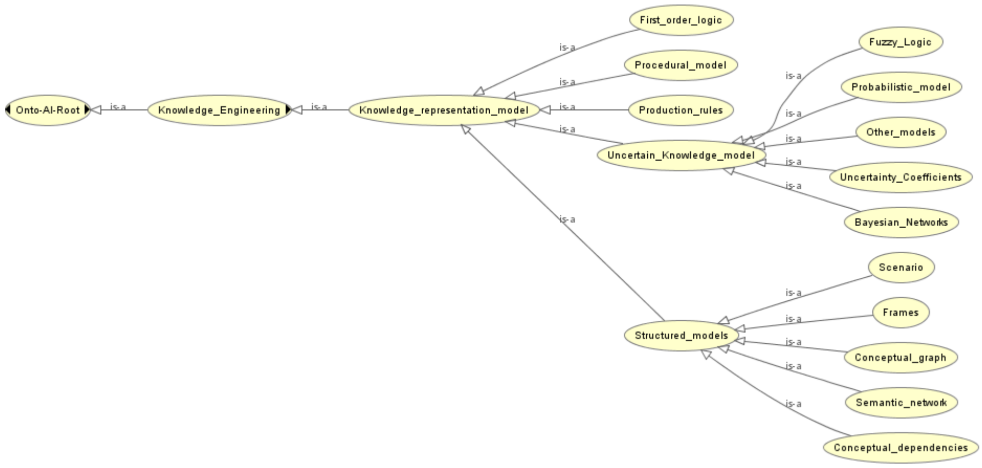


(b)

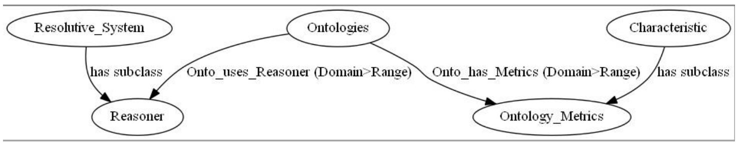
Figure 6. (a) A taxonomy for search strategies (in OWL Viz); (b) A knowledge graph for defining the lists Open and Closed used by search strategies (in GraphViz)

Three basic knowledge resources that are used for teaching and learning the subject of *Knowledge engineering* are shown in Figure 7. We have included a taxonomy for knowledge representation models used in AI and two knowledge graphs related to ontologies (specifying the resolutive system, the ontology evaluation metrics and the ontology terms).

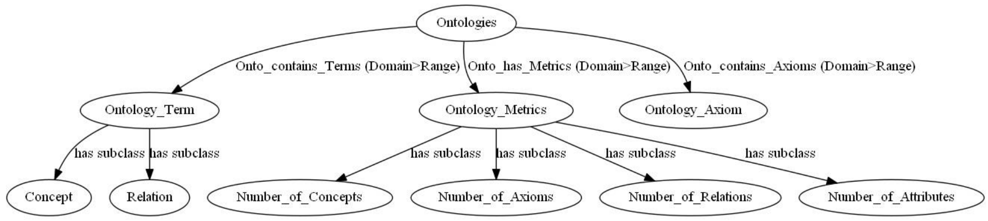
A knowledge graph that is used for teaching and learning the subject of *Knowledge based systems* is presented in Figure 8, including the components of a knowledge based system and the characteristics of a knowledge base.



(a)



(b)



(c)

Figure 7. (a) A taxonomy for knowledge representation models (in OWL Viz); (b) A knowledge graph related to ontologies resolutive system and performance evaluation (in GraphViz); (c) A knowledge graph for defining ontologies and specifying some metrics (in GraphViz).

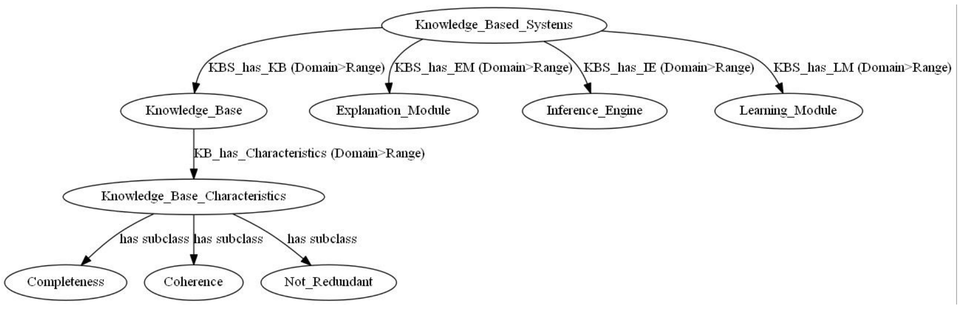


Figure 8. A knowledge graph related to knowledge based systems subject (in GraphViz)

The rule-based system reasoning algorithm is described as a procedural model.

A taxonomy that shows the software tools used to implement applications either at AI laboratory or AI project is presented in Figure 9.

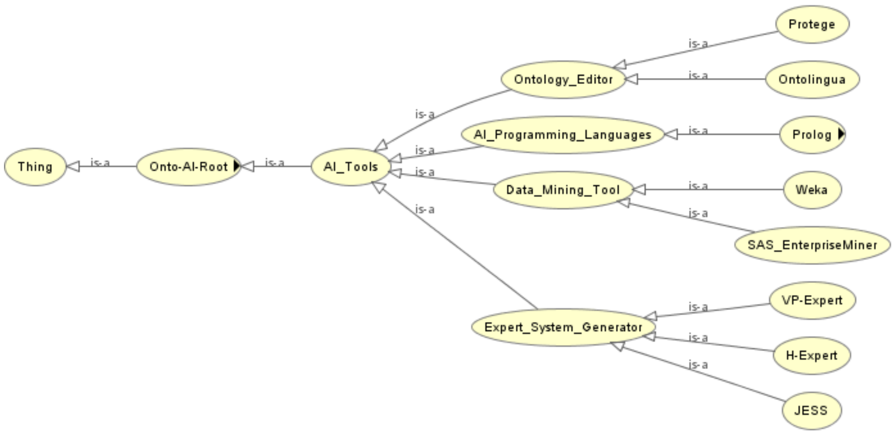


Figure 9. The taxonomy of AI tools included in the Onto-AI ontology (in OWL Viz)

In our case study, the inconsistencies of knowledge graphs were detected and solved by human experts (i.e. teachers) with the aid of Reasoner, the inference engine of Protégé.

So far, we have tested the Onto-AI ontology on a group of students during their fourth year of study at the AI project and AI laboratory work. The preliminary analysis revealed better marks at AI laboratory work assessment for those students that had chosen a topic on ontologies at the AI project, based on Onto-AI than those that had chosen a different topic (e.g. knowledge based systems) and did not use Onto-AI.

4. Conclusions and future work

Knowledge representation in computer-based educational systems is essential for increasing the efficiency of teaching and learning processes. The paper presented an overview on knowledge representation models that are or can be applied in higher education and described a case study of applying some models for the course of Artificial Intelligence teached to Computer Science undergraduate students at Petroleum-Gas University of Ploiesti. An OWL ontology, Onto-AI, was designed and implemented for this course, and examples of taxonomies and knowledge graphs were presented for specific AI course subjects. Procedural models were used for representing knowledge referring to algorithms such as BestFirst, A* or rule-based system reasoning.

The methodology followed in our research work can be applied to non-technical domains, as e.g. for a foreign language that students learn. The teacher can use knowledge graphs to explain the grammar of the language.

Despite of some problems that knowledge graphs can have (e.g. insufficient data, less explainability, incomplete, incorrect, or inconsistencies) they are an important educational visual resource that can improve the teaching and learning efficiency when more explanations are added and enough validated datasets are collected. Current trends include an extensive use of educational ontologies, knowledge graphs and large language models in higher education systems.

As a future work we shall extend the analysis of students' performance improvement when using the ontology and knowledge graphs for more groups of students that study the Artificial Intelligence discipline, from different specializations.

REFERENCES

Aytekin, M. C. & Saygin, Y. (2024) ACE: AI-assisted construction of educational knowledge graphs with prerequisite relations. *Journal of Educational Data Mining*. 16(2), 85-114.

Buitrago, M. & Chiappe, A. (2019) Representation of knowledge in digital educational environments: A systematic review of literature. *Australian Journal of Educational Technology*. 35(4), 46-62. doi: https://doi.org/10.14742/ajet.4041.

Fan, X., Sun, Y., Wang, Q. & Wang, X. (2024) Research on the application of knowledge graph in higher education of art and design. In: Kaki, S. et al. (eds). *Proceedings of the 6th International Conference on Literature, Art and Human Development, ICLAHD 2024*. Advances in Social, Education and Humanities Research 885, pp. 494-501. https://doi.org/10.2991/978-2-38476-319-1_57.

Hu, B., Zhu, J., Pei, Y. & Gu, X. (2025) Exploring the potential of LLM to enhance teaching plans through teaching simulation. *npj Science of Learning*. 10(7). https://doi.org/10.1038/s41539-025-00300-x.

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y-S., Kay, J., Knight, S., Martinéz-Maldonado, R., Sadiz, S. & Gašević, D. (2022) Explainable Artificial Intelligence in education. *Computers and Education: Artificial Intelligence*. 3, 100074. doi: https://doi.org/10.1016/j.caeai.2022.100074.

Kim, S.-Y., Görz, M. & Geisler, S. (2025) KONDA: An LLM-based tool for semantic annotation and knowledge graph creation using ontologies for research data. *Proceedings of the 5th International Workshop on Scientific Knowledge: Representation, Discovery, and Assessment, November 2025, Nara, Japan*.

Minsky, M. (1975) A framework for representing knowledge. Winston, P. (ed). *The Psychology of Computer Vision*. McGraw-Hill.

Nagowah, S., Ben Sta, H. & Gobin-Rahimbux, B. (2025) Conceptual knowledge representation: a semantic model for smart learning environments in an IoT-enabled smart campus. *Journal of e-Learning Knowledge Society*. 21(2), 44-60. https://doi.org/10.20368/1971-8829/1136004.

Pearl, J. (1988) *Probabilistic reasoning in intelligent systems*. Morgan Kaufman.

Piriyapongpipat, P., Goldin, S. & Ditcharoen, N. (2024) An alternative approach to ontology-based curriculum development in higher education. *Smart Learning Environments*. 11(20). https://doi.org/10.1186/s40561-024-00307-8.

Qin, Y., Cao, H. & Xue, L. (2020) Research and application of knowledge graph in teaching: Take the database course as an example. *Journal of Physics: Conference Series, ISEITCE 2020*. IOP Publishing. https://doi.org/10.1088/1742-6596/1607/1/012127.

Quillian, M. R. (1967) Word concepts: A theory and simulation of some basic semantic capabilities. *Behavioral Science*. 12, 410-430.

Ramazanova, V., Sambetbayeva, M., Serikbayeva, S., Sadirmekova, Z. & Yerimbetova, A. (2024) Development of a knowledge graph-based model for recommending MOOCs to supplement university educational programs in line with employer requirements. *IEEE Access*. 12, 193313-193331.

Reales, D., Manrique, R. & Grévisse, C. (2024) Core concept identification in educational resources via knowledge graphs and large language models. *SN Computer Science*. 5, 1029. https://doi.org/10.1007/s42979-024-03341-y.

Rizun, M. (2019) Knowledge graph application in education: a literature review. *Folia Oeconomica*. Acta Universitatis Lodziensis. 3(342). http://dx.doi.org/10.18778/0208-6018.342.01.

Russell, S. & Norvig, P. (2020) *Artificial intelligence: A modern approach*. 4th edition. Pearson, New York.

Schank, R. C. & Abelson, R. P. (1977) *Scripts, plans, goals and understanding: An inquiry into human knowledge structures*. Lawrence Erlbaum Associates.

Serles, U. & Fensel, D. (2024) *An introduction to knowledge graphs*. Springer.

Shi, Y., Yu, K., Dong, Y. & Chen, F. (2026) Large language models in education: a systematic review of empirical applications, benefits and challenges. *Computers and Education: Artificial Intelligence*. 10. https://doi.org/doi:10.1016/j.caeai.2025.100529.

Siew, C. S. Q. (2022) Investigating cognitive network models of learners' knowledge representations. *Journal of Learning Analytics*. 9(1), 120-129. https://doi.org/10.18608/jla.2022.7671.

Sowa, J. F. (2008) Conceptual graphs. In: van Harmelen, F., Lifschitz, V. & Porter, B. (eds) *Handbook of knowledge representation*, Elsevier, chapter 5, pp. 213-237.

Staab, S. & Studer, R. (2009) *Handbook on ontologies*. Springer.

Tiwari S., Al-Aswadi, F. N. & Gaurav, D. (2021) Recent trends in knowledge graphs: theory and practice. *Soft Computing*. 25, 8337-8355. https://doi.org/10.1007/s00500-021-05756-8.

van Harmelen, F., Lifschitz, V. & Porter, B. (eds) (2008) *Handbook of knowledge representation*. Elsevier.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł. & Polosukhin, I. (2017) Attention is all you need. *Proceedings of the 31st Conference on Neural Information Processing Systems, NIPS 2017, Long Beach, CA, USA*.

Wang, X., Chen, Z., Wang, H., Hou, U. L., Li, Z., & Guo, W. (2025a) Large language model enhanced knowledge representation learning: A survey. *Data Science and Engineering*. 10, 315-338. https://doi.org/10.1007/s41019-025-00285-y.

Wang, Q., Hou, S., Wan, S., Feng, X. & Feng, H. (2025b) Applying knowledge graphs to interdisciplinary higher education. *European Journal of Education Research*, 60(2). https://doi.org/10.1111/ejed.70078.

Xu, H., Gan, W., Qi, Z., Wu, J. & Yu, P. S. (2024) *Large language models for education: A survey*. https://doi.org/10.48550/arXiv.2405.13001.

Zadeh, L. (1965) Fuzzy sets. *Information and Control*. 8(3), 338-353.