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An Analysis of Knowledge Organization and Semantic Processing of Educational Texts Using Artificial Intelligence Technologies

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Abstract - **Educational institutions produce vast amounts of text-based resources such as textbooks, courseware, lectures, syllabi, digital learning resources, etc., posing problems related to effective knowledge organization, searching and semantically analyzing those. The conventional text organization techniques tend to be incapable of capturing complicated conceptual relations, context-dependent meanings and instructional structure inherent in the large educational corpus. This paper will examine the part that artificial intelligence (AI) plays in knowledge organization and semantically analyzing educational texts using a comprehensive conceptual framework. The framework proposed here contains a four-layer system with the following layers: data acquisition & preprocessing, semantic features extraction, knowledge organization, and intelligent application. The proposed framework incorporates natural language processing, ontology-based knowledge representation, knowledge graph, and deep learning for semantic analysis for efficient educational content management. The comparison of symbolic ontology-based approaches, statistical embedding-based approaches, and hybrid approaches is provided with regard to interpretability, scalability, semantic understanding, maintenance, ability to map to the curriculum, and explainability. The study shows that ontology-based systems exhibit interpretability and structured knowledge representation, while embedding-based systems show better scalability and context comprehension. Hybrid systems are able to leverage the benefits of both approaches through integration of deep learning-enabled semantic extraction with structured knowledge representations. These results demonstrate that hybrid AI-enabled architectures can be seen as a feasible way to build scalable, interpretable, and semantically coherent educational knowledge management systems. Some future directions of research on the topic have been also outlined, such as multilingual processing of educational text, interpretable semantic models based on AI, privacy-preserving knowledge management, and empirical evaluation on big educational data sets.**

Keywords: **Knowledge Organization, Semantic Processing, Educational Text, Artificial Intelligence, Natural Language Processing, Knowledge Graph, Ontology**

I. INTRODUCTION

Educational organizations worldwide create and process large volumes of text documents, from printed textbooks and digitized lecture notes to online course descriptions and question banks. The efficiency of using this documentation for educational purposes depends heavily on its indexing and semantic analysis (Alsharifi, 2023). Artificial intelligence (AI) technology has found increasing application in education for personalized learning, automated assessment, and intelligent document management (Zawacki-Richter et al., 2019). According to recent systematic studies, AI-based solutions are being adopted rapidly for learning, teaching, assessing, and managing, along with issues related to interoperability, data quality, and pedagogy (Chiu et al., 2023).

The concept of knowledge organization, stemming from library and information science, is understood as a method of structuring concepts, terms, and relations necessary for efficient retrieval, comparison, and reasoning about

information resources. In an educational setting, this concept is expanded to include the process of structuring curricula, learning goals, and the interrelationships between topics taught in a course. Ontological representations were extensively used to describe domain knowledge in the context of e-learning as the machine-readable representation that facilitates content organization and retrieval (Gil & Martin-Bautista, 2012; Mouromtsev et al., 2013). Further development of this approach includes the use of test-generation and content-alignment tools based on ontologies (Sirota & Liskin, 2015a; Sirota & Liskin, 2015b).

At the same time, semantic processing approaches, based on natural language processing, have made great progress due to the rapid development in deep learning and contextual language modeling. The application of transformer-based architectures, in particular those using bidirectional attention mechanism, significantly improved performance of text classification and entity recognition, as well as semantics comparison (Malek, 2025; Minaee et al., 2021; Devlin et al., 2019). Together with structured knowledge representation (such as knowledge graphs), semantic processing allows for more detailed analysis of educational texts and enables tasks like concept extraction, curriculum mapping, and personalization of content recommendations (Abu-Salih & Alotaibi, 2024; Garzón et al., 2025).

Nevertheless, the mentioned advances have not helped to bridge the gap that exists between the interpretability and structure inherent to symbolic approaches to knowledge representation and the scalability and context-sensitivity associated with statistical semantic processing approaches. Relatively few integrated frameworks combine both the paradigms mentioned above in order to deal with educational texts, while comparative analyses of the combination of these two approaches are distributed throughout computer science, library science, and educational technology literatures (Li et al., 2022). In this regard, this research paper attempts to fill in the gap by providing an integrated conceptual framework for the organization and semantic processing of educational texts with the help of artificial intelligence technologies (Chiu et al., 2023).

The structure of the paper includes: In Section 1, the background and aim of the research are presented. Section 2 is devoted to reviewing studies that have been done in the areas of artificial intelligence, knowledge structuring, semantic processing, and educational applications. Section 3 describes the methodology and four-layer AI-based architecture of the paper. Section 4 compares symbolic, statistical, and hybrid techniques. Section 5 contains conclusions and recommendations for the further research.

II. Literature Review

2.1 Artificial Intelligence Adoption in Education

There have been significant advancements in the implementation of AI technology in education within the last decade, including intelligent tutoring, automatic assessment, learning analytics, and content management. Systematic review conducted on applications of AI in higher education suggests that AI is commonly used in the fields of profiling and prediction, assessment and evaluation, adaptive system, and intelligent tutoring, while it is observed that there is lack of ethical and pedagogical reflection among educators (Zawacki-Richter et al., 2019). In addition, another systematic review carried out on learning, teaching, assessment, and administrative functions revealed thirteen different uses of AI technologies and ten key challenges in these uses, including issues of data governance, algorithmic transparency, and need for pedagogically-oriented designs (Malek, 2025). Literature surveys on AI-in-education literature suggest increase in the number of publications in recent years after 2019 with an emerging focus on generative AI tools (Li et al., 2022).

2.2 Knowledge Organization through Ontology-Based Systems

The field of ontology engineering is one of the core approaches used to organize knowledge in computer-assisted learning systems. Formal ontologies are used to describe the educational materials, learning objects, and their relationships in machine-readable format, thus allowing semantic search and reasoning over instructionally-related content. The knowledge-support model which is based on the approach of ontology learning illustrated how relational databases could be converted into continually evolving ontological systems for organizational knowledge management and could be applied to education as well (Gil & Martin-Bautista, 2012). In a similar vein, the ontology-based e-learning system which was created due to the lack of structuring of the educational materials proved how knowledge models could be used to create the united structure of fragmented digital learning content (Khan & Malik, 2026). Ontology-based engines were further utilized to produce assessment questions which correlated with the test content and course theory, hence showing that the use of formal knowledge representation goes beyond cataloging and could be actively employed for instructional purposes (Sirota & Liskin, 2015a; Sirota & Liskin, 2015b).

2.3 Semantic Processing, Text Classification, and Knowledge Graphs

Deep learning advancements have revolutionized the field of text semantics by shifting from the use of shallow lexical approaches to using contextual transformer-based embedding. Deep learning-based text classification literature highlights remarkable improvements in accuracy for sentiment analysis, topic classification, and question classification with the use of contextual embedding as opposed to the bag-of-words approach (Minaee et al., 2021; Al Faraby & Romadhony, 2024). Bidirectional transformers, in particular, have become a key component of semantic processing due to their improved ability to capture word meaning in context compared to sequential models that were previously used (Devlin et al., 2019). In the specific domain of education, the use of language models to perform the

classification and generation of examination questions has seen applications such as automated item banking and alignment with the cognitive taxonomy (Goh et al., 2023). On the other hand, examination questions classification through semantic similarity based on lexical database have been implemented in education (Subha et al., 2023).

Knowledge graphs improve upon semantic processing by organizing the extracted concepts and relations between them into a structured form. Systematic review of knowledge graph creation and application in the field of education revealed curriculum design, concept mapping, and personalized recommendation as leading application areas along with the problem of knowledge graph completeness and domain adaptation (Abu-Salih & Alotaibi, 2024). The parallel study of contextual knowledge graph construction for personalized recommendations provided insight on how text mining and semantic graph completion can be combined to model the relationship between learner and content (Garzón et al., 2025). Hybrid deep learning models for personalized course recommendations provide an example of how learning content can be represented semantically for personalized educational services (Ahadi et al., 2022). Bibliometric review of text mining applications in education provides an understanding of a larger developing field that includes sentiment analysis, topic modeling, and automatic structuring of educational corpora (Mustafa et al., 2024).

2.4 Conversational Agents and Intelligent Tutoring for Educational Text Interaction

Moreover, capabilities for semantic processing have been integrated into conversational and tutoring systems to interact with the learner via natural language. Roadmap analysis, consolidating several literature reviews in AI in education field pointed to conversational agents and intelligent tutoring as to one of the dynamically evolving areas, while pointing to insufficient longitudinal data concerning learning outcomes in the studies analyzed (Kalaivanai, 2026). Domain-specific applications, e.g., AI-assisted engineering education also note increasing use of natural language interaction for formative assessment and content delivery, similar trends can be seen in the reviews of AI in science education (Almasri, 2024; Wollny et al., 2021). Review of educational chatbots noted their usage for administrative, informative and pedagogical purposes and suggested alignment between chatbot evaluation and instruction goals as the research question (Davar et al., 2025). The following review of the challenges and opportunities related to the implementation of AI chatbots highlighted issues associated with data protection, reliability of responses, and overdependence by the learner (Essel et al., 2022). The empirical testing of a virtual teaching assistant chatbot in a higher educational environment found significant improvements in learning outcomes compared to traditional instruction alone, providing empirical evidence of the learning effectiveness of chatbots with semantic capabilities (Albornoz-De Luise et al., 2023). Other studies related to conversational architectures in intelligent tutoring systems have explored ways of supporting more effective conversations (Dharmireddi et al., 2025).

2.5 Regional Perspectives on AI-Enabled Educational Transformation

In addition to general tendencies, research specific to particular regions may offer useful information about the actual conditions in which knowledge organization and semantic processing technologies have been deployed. The research conducted on the effect of innovation and digitalization on the quality of higher education at a technical university of Uzbekistan showed a very positive perception by students, teachers, and administration of the role of digital technologies in education. Another study conducted on the issue of the AI-assisted transformation of the higher education management system in Uzbekistan stated that despite the early stage of development of the AI infrastructure, due to governmental support and investments in the digital infrastructure, the conditions for the deployment of such technology become increasingly favorable, while there remain challenges associated with the availability of qualified personnel and data governance (Arvind & Rao, 2025; Muhabbat et al., 2024).

III. METHODOLOGY

This research utilizes the conceptual and comparative approach instead of conducting an experiment based on one particular data set. The aim is to develop an adequate architecture for structuring and semantic processing of educational texts via AI technologies and to compare existing approaches within common criteria. Methodology consists of three stages: developing architecture, selecting representatives of the methods, and comparison of those methods.

At the first stage, the four-layer architecture was developed based on the analysis of the structural patterns that have been recurrently found in knowledge organization systems driven by ontologies and knowledge graph generation pipelines used in education described in fig. 1. Systems based on ontologies in education usually proceed from content acquisition to knowledge representation via concept and relation extraction and querying at the application level. Education-based pipelines for knowledge graphs development also go through a similar path starting from text mining and entity extraction and finishing with graph reasoning and downstream applications.

Layer 1, Data Acquisition & Preprocessing, includes the acquisition of educational text from sources such as textbooks, syllabi, transcripts of lectures, and digital archives, followed by steps like tokenization, normalization, stop-word filtering, parts-of-speech tagging, and sentence splitting. Layer 2, Semantic Feature Extraction, includes contextual embedding approaches for obtaining semantic vectors at the sentence and document levels, along with named entity and keyphrase extraction to filter out relevant concepts. Layer 3, Knowledge Organization, entails mapping

the identified concepts onto existing or evolving ontology or taxonomy, identifying relations between concepts, and forming a knowledge graph that respects curricula hierarchies. The Layer 4, Intelligent Application Layer, includes application of the organized knowledge base for semantic search, personalized content recommendations, automated mapping of curriculum, and NLP-based conversation and tutoring interfaces. A feedback loop, including evaluation and refinement based on accuracy and relevance metrics along with domain-expert validation, allows for refining the semantic models and knowledge structures in Layers 2 and 3 using new educational text.

Representative techniques belonging to each category were identified in the literature review and then assigned to one of three main categories in the third phase of the taxonomy development: symbolic approaches, statistical approaches, or hybrid approaches (both symbolic and statistical). These categories are distinguished according to the primary means of knowledge representation presented in each article.

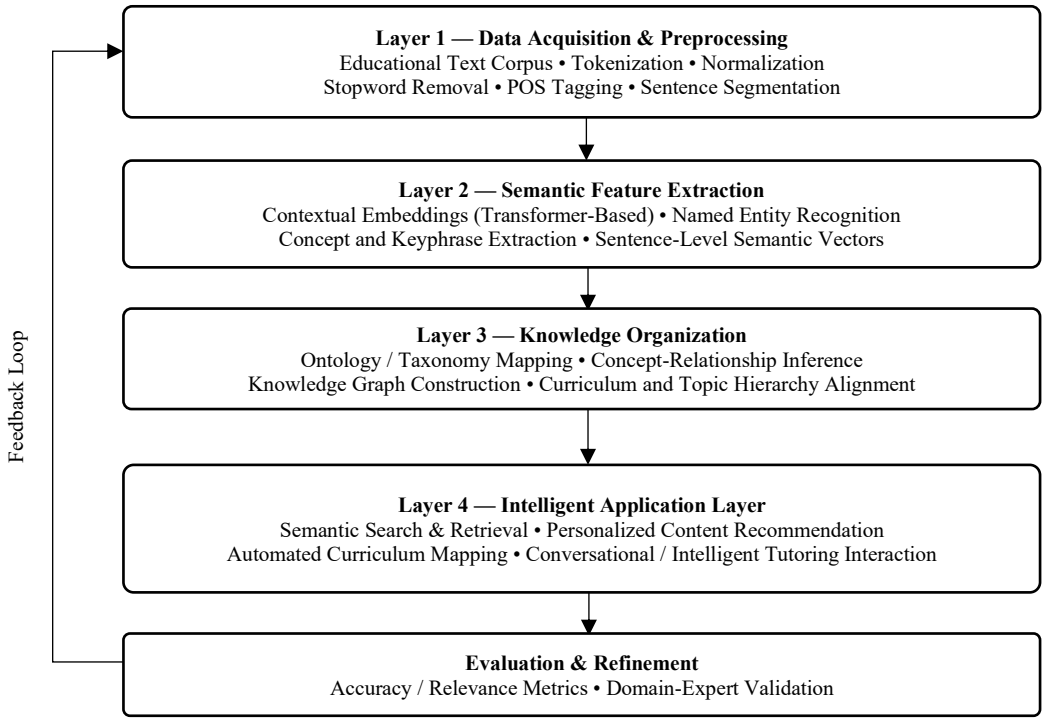


Fig. 1 Four-Layer Architecture for AI-Based Knowledge Organization and Semantic Processing of Educational Texts

During the third phase, the three groups were compared on the basis of six criteria that were considered to be relevant to the use of the systems in education. The criteria have been selected on the basis of concerns mentioned in the literature repeatedly about the use of such knowledge systems in the domain of instruction using artificial intelligence. The findings of the comparison are discussed in Section 4.

IV. Comparative Analysis

A comparison of the three approaches mentioned above regarding the organization and semantic processing of education-related text is presented in table I on the basis of the six criteria outlined in Section 3.

TABLE I COMPARATIVE ANALYSIS OF AI-BASED KNOWLEDGE ORGANIZATION AND SEMANTIC PROCESSING APPROACHES

Dimension	Ontology-based (Symbolic)	Embedding-based (Statistical)	Hybrid approach
Interpretability	High — explicit concept relations	Low — distributed vector representations	Moderate to high
Scalability to large corpora	Limited — manual/semi-automatic curation	High — automated processing	High
Semantic granularity	Coarse to moderate	Fine-grained, context-sensitive	Fine-grained with structure
Maintenance effort	High — ontology updates required	Moderate — retraining needed	Moderate
Suitability for curriculum mapping	Strong for formal hierarchies	Weak without external structure	Strong
Explainability of output	Transparent	Opaque without post-hoc methods	Improved via structured overlay

This comparison shows that ontology-based systems have the highest level of interpretability and perfectly fit into the hierarchy of curricula, but the cost of creation and maintenance of such systems is high, which makes them unscalable to larger and constantly evolving educational datasets. Embedding-based systems are scalable and able to capture more subtle context information, but generate hard-to-interpret and unstructured outputs unless additional post-processing is applied.

TABLE II COMPARATIVE CAPABILITY SCORES OF AI-BASED KNOWLEDGE ORGANIZATION APPROACHES

Dimension	Ontology-Based	Embedding-Based	Hybrid Approach
Interpretability	5	2	4
Scalability	2	5	5
Semantic Granularity	3	5	5
Maintenance Efficiency	2	3	4
Curriculum Mapping	5	2	5
Explainability	5	2	4

A comparative analysis of ontology-based, embedding-based, and hybrid AI systems based on different aspects of knowledge organization is shown in table II. As can be seen from the results obtained, ontology-based techniques ensure high levels of interpretability and curriculum fit, whereas embedding-based techniques exhibit better performance in terms of scalability and semantics comprehension.

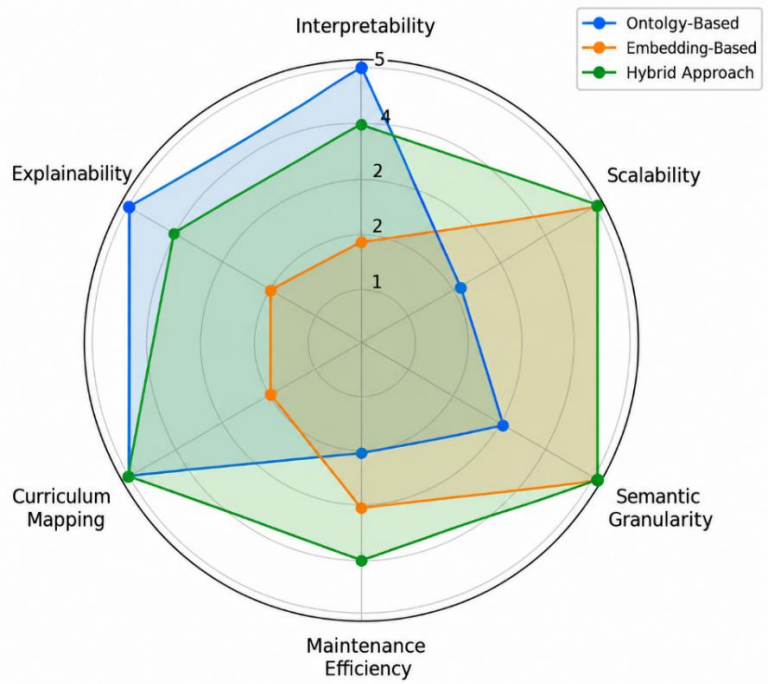


Fig. 2 Comparative Capability Analysis of AI-Based Knowledge Organization Approaches

Fig. 2 is a visualization of the relative strengths of ontology-based, embedding-based, and hybrid AI approaches according to several important characteristics such as interpretability, scalability, semantic granularity, maintenance, curriculum alignment, and explainability. The fig. 2 demonstrates how hybrid approaches have a balanced capacity because they combine structured and scalable semantics.

Hybrid systems that rely on the use of embedding-based semantic features extraction to enrich ontologies and knowledge graphs provide a compromise between all the discussed criteria. They combine scalability and sensitivity to context of statistical systems with at least partial structure and interpretability of output through the underlying ontology/knowledge graph. This is consistent with the architectural model introduced in Section 3, where semantic feature extraction layer (Layer 2) directly feeds the knowledge organization layer (Layer 3), and also explains why hybrid systems become increasingly popular in modern knowledge graph development in education.

V. DISCUSSION

The comparative analysis and architectural considerations in this paper show that the organization and semantics of educational text can be effectively achieved through hybrid approaches combining the interpretability of symbolic knowledge representation with scalability and context-awareness of statistical language models. This approach is in line with general trends noted in systematic

surveys of AI technologies for education, which have shown the growing integration of various AI methods in a single educational system rather than the use of one single technology (Malek, 2025)17]. The use of text mining and semantic graph completion in constructing knowledge graphs in education is another example of such trend (Abu-Salih & Alotaibi, 2024; Garzón et al., 2025).

There are a number of implications for practice emerging from this discussion. Firstly, designers of curriculum and developers of digital resources aiming at introducing semantic search and recommendation services over educational text corpora could consider using a layered approach like the one presented in Section 3, instead of relying exclusively on symbolic and statistical approaches. Secondly, the effectiveness of the transformer models for extracting semantic features in text classification and question classification tasks makes them a good choice for the feature extraction layer in educational knowledge systems, especially if there are means for the structural interpretation of extracted features (Minaee et al., 2021; Devlin et al., 2019; Goh et al., 2023; Subha et al., 2023). Thirdly, the recent research on conversational and tutoring systems shows that semantically structured educational knowledge corpora can be effectively used in natural language interaction with learners, while the tools for evaluation of such systems are still lacking (Davar et al., 2025; Essel et al., 2022; Albornoz-De Luise et al., 2023; Dharmireddi et al., 2025).

The analysis of regional data presented in Section 2.5 further suggests that the successful implementation of these technologies is contingent on certain institutional and infrastructural factors. The favorable attitudes toward digitalization expressed by both personnel and students at a technical university in Uzbekistan may reflect a supportive environment for AI-based tools of organizing knowledge. At the same time, the recognition of the need for additional skilled personnel and initial AI infrastructure in a country may suggest that technological solutions should be complemented by corresponding investments in human resources (Senthil et al., 2022). These findings corroborate a larger trend identified in the literature according to which the issues related to AI in education are largely organizational and pedagogical rather than technical (Zawacki-Richter et al., 2019; Malek, 2025).

There are several aspects to note regarding potential limitations. First of all, the comparison of the approaches described in this paper is based on the categorization of the available information rather than a controlled empirical evaluation based on the same dataset; thus, the comparison based on the criteria specified in table I can be viewed as a qualitative one. Moreover, the selected papers are related to different educational levels, languages, and settings. Future research can overcome the aforementioned limitations through the implementation of the proposed four-layered architecture on a multilingual educational text dataset and its further evaluation from the perspective of retrieval accuracy, curriculum alignment, and learner results. Another aspect that is worth considering in the future refers to the development of the approaches to explainability of the embedding-based components as well as the data privacy frameworks.

VI. Conclusion

This research has studied the capability of artificial intelligence technologies in enhancing knowledge structuring and semantic processing of educational text. The research has taken care of the drawbacks faced by the traditional methods of educational text management that are not able to accommodate the conceptual, contextual, and instructional structuring of the text. Four conceptual levels have been proposed for knowledge structuring and semantic processing of the educational text including data acquisition and pre-processing, semantic feature extraction, knowledge structuring, and intelligent applications. The comparison has shown that the ontology-based approaches have high interpretability and effectiveness in curriculum alignment but have scalability and maintenance issues. At the same time, embedding-based approaches have high levels of contextual understanding and scalability but can lack transparency. The hybrid approaches that combine transformer-based semantic extraction with the ontology and knowledge graph models can be considered a good compromise because they unite scalability, contextual understanding, and interpretability. Thus, the research has proven that the hybrid artificial intelligence architecture is applicable to creating educational knowledge management platforms, including semantic search systems, personal recommendation tools, automated curriculum mapping, and intelligent tutoring systems. Yet, the study is restricted due to the fact that it is conceptual and comparative in nature rather than being validated experimentally on a popular educational dataset. Further work should see the use of the suggested approach on multilingual educational corpora and analysis of its effectiveness based on such criteria as accuracy of the retrieval process, consistency of the semantics, curricular compatibility, and learning outcomes of students. In addition, further work is needed to make AI models more explainable, ensure data privacy, and create adaptive knowledge structures that would be able to cope with dynamically changing educational situations.

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