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A Knowledge Graph-Based Neuro-Symbolic Conceptual Architecture for Semantic Learner Modeling in Intelligent Tutoring Systems

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ABSTRACT

Intelligent Tutoring Systems (ITSs) require accurate and semantic modeling of learner states to deliver personalized learning experiences. Despite advances in the application of ontologies and knowledge graphs in educational systems, existing approaches are generally based either on symbolic methods, which offer high interpretability but have limited flexibility in handling dynamic data and complex learner interactions, or on data-driven approaches, which are capable of extracting behavioral patterns but often lack sufficient semantic transparency and explainability. This paper proposes a knowledge graph-based neuro-symbolic conceptual architecture for semantic learner modeling in Intelligent Tutoring Systems. In the proposed architecture, the data-driven component is responsible for analyzing learner interactions and extracting patterns related to learning states, whereas the symbolic component employs ontologies and knowledge graphs to organize educational knowledge, maintain semantic consistency, and support interpretable reasoning. The architecture's integration mechanism is designed to use the results of learner data analysis to update and enrich the learner model within the knowledge graph. Subsequently, the symbolic layer employs semantic rules and conceptual relationships to generate adaptive instructional recommendations. The proposed architecture is organized as a five-layer framework, providing a conceptual foundation for developing Intelligent Tutoring Systems with enhanced explainability, semantic consistency, and adaptability. By combining the strengths of data-driven and symbolic approaches, this framework seeks to reduce the gap between learner data analytics and semantic reasoning in intelligent educational environments.

1. INTRODUCTION

Intelligent Tutoring Systems (ITSs) are among the important application domains of artificial intelligence in education. They are designed to provide personalized learning experiences adapted to learners' needs, prior knowledge, and individual characteristics [1]. Intelligent Tutoring Systems emerged in the 1970s with the development and successful implementation of knowledge-based systems and expert systems [9]. Unlike traditional educational systems, which generally provide the same content to all learners, an ITS seeks to analyze the learner's

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state and deliver appropriate educational content, personalized learning pathways, and targeted instructional feedback at the appropriate time [2, 3].

Within this context, Learner Modeling is regarded as a central component in the design and operation of Intelligent Tutoring Systems. This process involves extracting, representing, and updating characteristics such as the learner's current knowledge level, degree of mastery of concepts, learning progress, and other indicators related to the learner's state. The accuracy and richness of the learner model play an important role in the quality of instructional decisions and the adaptability of the system [4, 11, 13, 16].

In recent years, the application of Semantic Web technologies in Intelligent Tutoring Systems has attracted considerable attention. In this approach, technologies such as ontologies, Linked Data, and Knowledge Graphs are employed to create structured representations of educational knowledge and learner characteristics [1, 2, 4, 5, 8, 12]. In particular, knowledge graphs can serve as the semantic core of an educational system by enabling the modeling of educational concepts, prerequisite relationships, and connections among different elements of the learning environment, while also providing a foundation for knowledge-based inference [5].

Despite these advances, a review of the literature indicates that existing approaches to semantic learner modeling can generally be classified into two broad categories. The first comprises symbolic approaches, which are based on ontologies, logical rules, and explicit knowledge representation. These approaches generally provide a high level of interpretability and enable knowledge-based inference; however, they may have limited flexibility when dealing with dynamic behavioral data and complex patterns of learner interaction [1, 4]. In contrast, data-driven approaches rely on the analysis of learner interaction and behavioral data to extract learning patterns and can perform effectively in identifying behavioral trends and patterns [4, 6, 7, 11, 13, 16]. Nevertheless, the knowledge extracted through these methods is often not explicitly represented in semantic form, making the interpretation of educational and conceptual relationships challenging [11, 16]. Accordingly, recent research has emphasized the development of explainable models for knowledge tracing so that the reasons underlying a learner's state can be transparently explained [16].

In this study, the term "Neuro-Symbolic" is used in a general sense to refer to the integration of data-driven and symbolic components and does not necessarily imply the use of a specific type of neural network. Within the proposed architecture, the term represents a combination of data-driven analytical methods which may include statistical methods, machine learning, or deep learning and symbolic reasoning methods based on ontologies and knowledge graphs. Neuro-symbolic approaches have recently emerged as a promising research direction in the field of Intelligent Tutoring Systems [10, 15, 17, 18]. In other words, "neuro" here refers to any type of data-driven analytical component capable of extracting behavioral patterns rather than necessarily referring to a particular neural network. This broad definition also allows the data-driven component to be replaced by different algorithms in future implementations.

This situation indicates a research gap in the field of learner modeling, particularly regarding the lack of frameworks capable of simultaneously exploiting the semantic representation capabilities of knowledge graphs and the pattern-extraction capabilities of data-driven approaches. In response to this challenge, the present study proposes a knowledge graph-based neuro-symbolic conceptual architecture for semantic learner modeling in Intelligent Tutoring Systems. In this architecture, the data-driven component analyzes learner interactions and extracts indicators and patterns associated with the learner's learning state, whereas the symbolic component, relying on ontologies and knowledge graphs, is responsible for organizing knowledge, maintaining semantic consistency, and supporting interpretable reasoning. Furthermore, the integration mechanism is designed so that the results of data analysis can be used to update the learner's semantic model within the knowledge graph, thereby providing a foundation for supporting instructional decisions and recommendations.

The proposed architecture is organized as a five-layer framework that covers the flow of information from learner interaction data to outputs supporting instructional decision-making. The remainder of the paper is organized as follows. First, the theoretical foundations and related studies in learner modeling and semantic approaches are reviewed in Section 2. Subsequently, the proposed architecture and its components, including its various layers and neuro-symbolic integration mechanism, are described in Section 3. Finally, the discussion, conclusions, and directions for future research are presented in Sections 4 and 5.

2. RELATED WORK

This section reviews studies related to semantic learner modeling in Intelligent Tutoring Systems. Based on an analysis of the existing literature, studies in this field can be categorized into three main research streams: (1) ontology- and Semantic Web-based approaches, (2) knowledge graph-based approaches and semantic recommender systems, and (3) data-driven and hybrid approaches. The purpose of this review is to explain the capabilities and limitations of each research stream and to clarify the position of the proposed architecture within this research landscape.

2.1. Ontology- and Semantic Web-Based Approaches

A substantial body of research on Intelligent Tutoring Systems has employed Semantic Web technologies to provide structured representations of educational knowledge and learner models. A comprehensive review in this area was conducted by Narimisaei (2021), which examined the application of concepts such as ontologies, the RDF data model, and Linked Data in e-learning systems. In these studies, technologies such as RDF, RDFS, and OWL have been employed to define educational concepts, learner characteristics, and relationships among them [1, 4, 8]. In addition, studies such as [9] have investigated the use of ontologies for modeling learner profiles and adapting educational content. Some studies have also proposed ontology-based recommender frameworks in which learning resources, metadata, learner profiles, and inference rules are organized within a coherent semantic structure [2]. In these approaches, content adaptation is primarily performed on the basis of conceptual relationships and constraints defined within the ontology. Furthermore, the use of knowledge graphs for modeling prerequisite and conceptual relationships among educational elements has received attention [3, 5]. These studies indicate that knowledge graphs can provide an appropriate foundation for organizing domain knowledge and supporting educational recommendations.

Despite these advantages, most of these approaches rely on predefined knowledge structures and relatively static rules. Consequently, they have limited flexibility when dealing with large volumes of interactive data and dynamic behavioral patterns and generally do not provide an explicit mechanism for extracting latent patterns from behavioral data. This limitation highlights the need for approaches capable of combining the strengths of semantic representation with the ability to analyze learner behavioral data.

2.2. Knowledge Graph-Based Approaches and Semantic Recommender Systems

In recent years, the use of knowledge graphs in intelligent educational systems has attracted increasing attention as a means of enriching content semantically and improving recommendation mechanisms. In these approaches, knowledge graphs are typically employed to model educational concepts, relationships among them, and semantic connections between learning resources. Such representations can facilitate the discovery of conceptual relationships and improve the retrieval and recommendation of educational resources.

For example, study [3] introduced a knowledge graph-based recommender framework incorporating a domain ontology, in which conceptual relationships among educational topics were used to improve the matching of learning resources. In another study [4], the ConceptNet knowledge graph was combined with deep learning models such as Long Short-Term Memory (LSTM) to provide semantic representations of content and predict appropriate educational resources. Similarly, study [7] employed the DBpedia knowledge graph together with Latent Semantic Analysis (LSA) to enrich conceptual information in educational recommender systems, particularly under sparse-information conditions.

Despite these advances, the primary focus of many of these studies has been on improving the quality of educational resource recommendations, while the learner model often plays only a limited role in the semantic structure of the system. In many cases, learner characteristics are represented as a simple profile or a set of input features rather than being modeled as part of a dynamic semantic structure within the knowledge graph. Consequently, the interaction between learner behavioral analysis and semantic knowledge representation is generally limited to specific stages of the recommendation process. An explicit and coherent mechanism for continuously updating the learner model within a knowledge graph framework has received comparatively limited attention.

2.3. Data-Driven and Hybrid Approaches to Learner Modeling

In recent years, the use of data-driven methods and machine learning for learner modeling in intelligent educational systems has increased substantially. These approaches analyze users' interactions with learning environments including study trajectories, responses to exercises, and behavioral patterns to extract indicators of learning state and learner mastery. Such methods have been particularly useful for identifying latent patterns in educational data and predicting learner performance.

Some studies have attempted to combine these data-driven approaches with semantic knowledge resources. For example, study [4] employed a combination of deep learning models and semantic knowledge resources to improve the recommendation of educational resources. Similarly, study [7] used knowledge graph-based semantic enrichment alongside data analysis methods to improve the performance of educational recommender systems, particularly under sparse-information conditions.

Despite these efforts, many of these approaches continue to face challenges concerning the interpretability and semantic representation of the extracted knowledge. In many cases, the outputs of data-driven models are represented as feature vectors or statistical parameters, and their relationships with conceptual structures in the knowledge domain are not explicitly modeled. Moreover, in some studies, the role of symbolic components is limited to the early stages of the process, such as data enrichment or preprocessing, without establishing deeper integration between behavioral data analysis and semantic knowledge representation. This issue demonstrates the continued need for frameworks capable of coherently integrating learning data analytics with knowledge graph-based semantic models for learner modeling.

2.4. Summary and Research Gap

The literature review indicates that each of the three major research streams ontology- and Semantic Web-based approaches [1, 2, 5], knowledge graph-based approaches and semantic recommender systems [3, 4, 7], and data-driven and hybrid approaches [4, 7] addresses only part of the learner-modeling problem. Symbolic approaches offer conceptual consistency, reasoning capabilities, and a high degree of interpretability, but they generally face limitations in adapting to dynamic data and complex behavioral patterns [1, 4]. Conversely, data-driven approaches are more capable of extracting patterns and predicting learner behavior, but they often lack explicit semantic representation and sufficient explanatory capabilities for end users [4, 7].

Although some studies have attempted to employ data-driven and semantic elements in combination [4, 7], the literature indicates that an integrated framework that simultaneously describes learner-interaction analysis, semantic learner-model updating, and interpretable instructional reasoning within a coherent conceptual architecture has received limited attention. Accordingly, the present study proposes a knowledge graph-based neuro-symbolic conceptual architecture that seeks to provide a framework in which the capabilities of learning-data analytics are combined with semantic representation and reasoning capabilities, thereby enabling more dynamic and interpretable learner modeling in Intelligent Tutoring Systems.

3. PROPOSED ARCHITECTURE: A LAYERED NEURO-SYMBOLIC FRAMEWORK BASED ON KNOWLEDGE GRAPHS

In light of the research gaps identified in the previous section, particularly the limitations of existing approaches in integrating learning-data analytics with semantic knowledge representation [1, 4, 7, 11], this study proposes a conceptual architecture for semantic learner modeling in Intelligent Tutoring Systems. The objective of this architecture is to provide an integrated framework for combining learner interaction data with semantic knowledge structures, thereby enabling learning-state analysis, interpretable reasoning, and support for instructional decision-making [10, 15]. Within this framework, the knowledge graph serves as the primary infrastructure for knowledge representation and the modeling of conceptual relationships, while data-driven methods are employed alongside it to analyze learner interactions [5, 12].

3.1. Overview

This study proposes a layered, knowledge graph-based conceptual architecture for semantic learner modeling in Intelligent Tutoring Systems. By leveraging Semantic Web technologies, particularly ontologies and knowledge graphs, together with learner-interaction data analytics, the architecture provides a framework for the semantic representation of learning states and supports interpretable reasoning [1, 5, 8]. In this study, the term "neuro-symbolic" is used in a general sense to refer to the integration of data-driven and symbolic components. Accordingly, depending on the implementation scenario, the data-driven component may employ statistical methods, machine learning, or deep learning techniques [4, 7, 10, 15].

The proposed architecture is organized as a five-layer framework that covers the flow of information from raw learner interaction data to the generation of adaptive instructional actions and recommendations (Figure 1). These layers are:

1. Data and Interaction Layer
2. Semantic Knowledge Core
3. Semantic Learner Representation Layer
4. Neuro-Symbolic Integration and Reasoning Layer
5. Adaptive Instructional Action Layer

As illustrated in Figure 1, the fourth layer serves as the core of the architecture and consists of two components: data-driven analytics and symbolic reasoning, which interact with one another through a feedback-based mechanism. This layered structure is consistent with recent research on neuro-symbolic architectures for Intelligent Tutoring Systems [10, 15, 17, 18]. The role and functionality of each layer in the proposed architecture are described in the following sections.

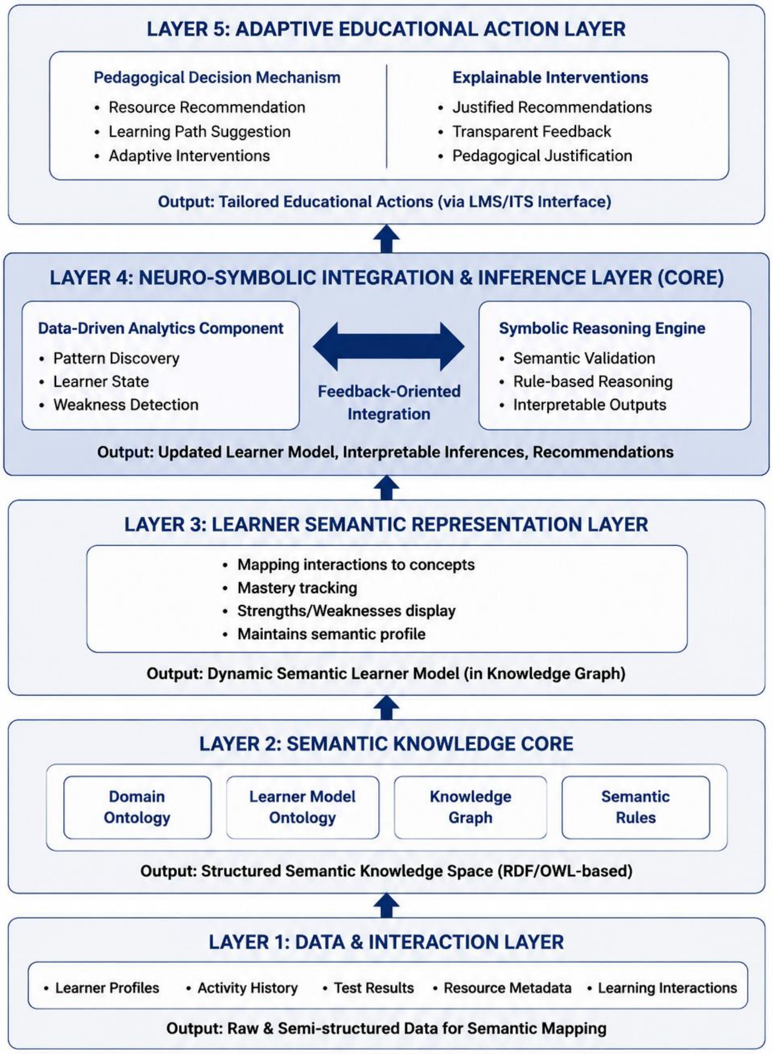

Fig. 1. Proposed Layered Neuro-Symbolic Architecture for Semantic Learner Modeling in Intelligent Tutoring Systems

3.2. Layer 1: Data and Interaction Layer

The Data and Interaction Layer is responsible for collecting and managing data associated with learner activities in digital learning environments. This layer collects various types of data, including learner profile information, interaction histories with the educational system, assessment and assignment results, and metadata associated with educational resources [4, 7]. These data may be obtained from multiple sources, such as Learning Management Systems (LMSs), assessment systems, and educational content repositories.

Following data collection, processes such as multi-source data integration, data cleaning, and initial preprocessing are performed to transform raw data into a form suitable for subsequent analysis [11, 13]. The output of this layer consists of structured or semi-structured data that can be mapped, in the higher layers of the architecture, to semantic representations associated with the learner model.

3.3. Layer 2: Semantic Knowledge Core

Following the provision of learner interaction data in the preceding layer, the Semantic Knowledge Core serves as the conceptual foundation of the architecture [1, 5, 8]. The primary purpose of this layer is to organize and represent educational knowledge and learner-related concepts in a structured manner, thereby establishing connections between learning data and the conceptual structure of the educational domain [12].

In this layer, domain knowledge is organized using a domain ontology and a learner-model ontology [1, 2, 5, 9]. The domain ontology explicitly defines the principal concepts of the learning domain, such as subject topics, skills, prerequisite relationships, and learning objectives. In contrast, the learner-model ontology describes learner-related characteristics, including knowledge level, degree of mastery of concepts, learning progress, and other relevant indicators.

These conceptual structures are integrated into a unified knowledge graph, in which relationships among educational concepts and learner characteristics are modeled as semantic entities and edges [3, 5, 12]. Such a structure enables the storage, linking, and querying of semantic data and provides an appropriate foundation for knowledge-based analysis and reasoning. In addition, a set of semantic rules and relationships can be employed to express constraints within the educational domain and support higher-level inference.

Overall, the primary function of this layer is to establish a structured semantic representation of educational knowledge and its associated conceptual relationships. The output of this layer serves as a central semantic knowledge base that is utilized by the higher layers of the architecture, particularly in the learner-model representation and educational reasoning processes.

3.4. Layer 3: Semantic Learner Representation Layer

Following the establishment of the semantic knowledge infrastructure in the preceding layer, the Semantic Learner Representation Layer is responsible for creating and maintaining the learner-model structure within the knowledge graph. At this layer, the learner's state is represented as a semantic model based on the learner's interactions with the educational environment and the conceptual structures defined in the ontologies [13, 16].

Within this framework, learner interactions with the educational system including completed activities, learning paths through educational content, responses, and assessment outcomes are mapped to corresponding educational concepts using the domain ontology [5]. This mapping process enables the transformation of raw behavioral data into semantic indicators, such as the learner's degree of mastery of individual concepts, progress in specific skills, and identified strengths and weaknesses. These indicators are represented as semantic entities and relationships within the knowledge graph [13].

In designing this layer, a distinction is made between the representation role and the learner-model updating role. The Semantic Learner Representation Layer is responsible for maintaining the structured representation of the learner's current state, whereas data analysis, indicator computation, and updating of this state are performed in the subsequent layer, namely the Neuro-Symbolic Integration and Reasoning Layer. This separation of responsibilities improves architectural clarity and enables the independent management of these processes.

The output of this layer is a dynamic semantic learner model represented in the knowledge graph as a set of nodes connected to educational concepts and relationships representing mastery, progress, and conceptual associations [3, 16]. This model serves as a primary information source for the higher layers of the architecture, particularly the reasoning layer and the adaptive instructional action layer.

3.5. Layer 4: Neuro-Symbolic Integration and Reasoning Layer

The Neuro-Symbolic Integration and Reasoning Layer constitutes the core of the proposed architecture [10, 15]. This layer is designed to combine data-driven analysis of learner interactions with reasoning based on semantic knowledge, thereby providing a foundation for simultaneously achieving adaptability and explainability in learner modeling. The layer consists of two principal components and an integration mechanism, which are described below. The use of dynamic knowledge graphs for learner modeling has also been emphasized in recent research, such as GraphMASAL [13].

The first component, Data-Driven Analytics, is responsible for processing learner interaction data and extracting patterns and indicators associated with the learning process. Using statistical methods, machine learning, or deep learning, this component can perform tasks such as identifying interaction patterns, analyzing learning states, detecting educational needs and weaknesses, and extracting implicit knowledge from behavioral data [4, 7, 11, 13]. The proposed architecture is designed so that the selection of a specific algorithm within this component is not architecture-dependent and can therefore be modified according to the implementation scenario.

The second component, Symbolic Reasoning, employs ontologies, semantic rules, and relationships represented in the knowledge graph to interpret and validate the outputs of the data-driven component. Its functions include semantic validation of data-driven outputs, application of instructional rules and domain constraints such as prerequisite checking inference of conceptual relationships, and generation of interpretable outputs for use by the instructional action layer [1, 2, 5, 9, 16].

The Feedback-Oriented Integration mechanism provides the communication bridge between these two components [10, 14]. Unlike cascading approaches, in which data-driven and symbolic components operate sequentially without feedback [4], the proposed architecture enables bidirectional interaction between the two components through a feedback-oriented integration mechanism. Within this mechanism, outputs from the data-driven component are used as evidence for updating the semantic learner model in the knowledge graph. Subsequently, the symbolic reasoning engine analyzes the applied changes based on semantic rules and conceptual relationships and generates interpretable results [15].

Furthermore, reasoning outputs can contribute, at the conceptual level, to enriching and refining the learner model during subsequent analytical cycles. However, this feedback does not necessarily imply the existence of a fully automated closed learning loop at the implementation level; rather, it is conceptualized primarily at the architectural design level.

The output of this layer consists of three components:

1. An updated semantic learner model;
2. Interpretable instructional inferences; and
3. Decision Support Signals, which are transformed into adaptive instructional actions in the subsequent layer.

3.6. Layer 5: Adaptive Instructional Action Layer

Following the generation of interpretable inferences and knowledge-based recommendations in the Neuro-Symbolic Integration and Reasoning Layer, the Adaptive Instructional Action Layer is responsible for transforming these outputs into practical educational decisions and services. This layer constitutes the final operational stage of the proposed architecture and aims to provide personalized instructional interventions aligned with the learner's semantic state, identified needs, and learning objectives [15].

As illustrated in Figure 2, a learner interaction event originates in the Data and Interaction Layer (Layer 1), is transformed into a semantic representation using the Semantic Knowledge Core (Layer 2), and is subsequently analyzed and interpreted in the Neuro-Symbolic Integration and Reasoning Layer (Layer 4). Finally, the resulting information leads to an adaptive instructional action in Layer 5. This data flow is consistent with recent research on neuro-symbolic architectures for Intelligent Tutoring Systems [10, 15, 17, 18].

At this layer, a Pedagogical Decision Mechanism uses the inferences generated in the preceding layer, together with instructional rules and learning objectives, to select the most appropriate instructional actions for each learner. This mechanism transforms knowledge-based recommendations into practical interventions within the learning environment.

The generated actions may include recommending educational resources and activities appropriate to the learner's mastery level, suggesting learning paths or instructional sequences consistent with conceptual prerequisites, generating personalized feedback, and providing targeted instructional interventions such as remedial exercises, adjustment of difficulty levels, or notification of an instructor when additional support is required [3, 4, 6, 12, 14].

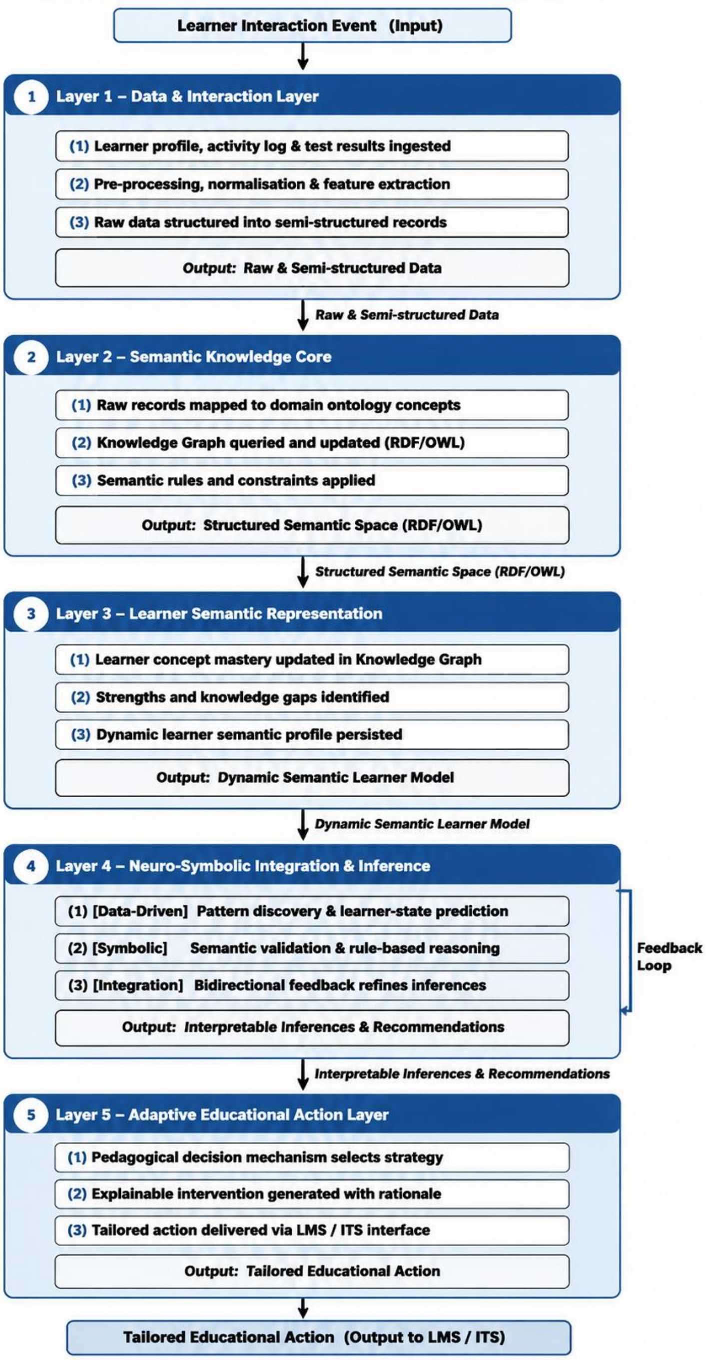

Fig. 2. Data Flow and Interaction Sequence in the Proposed Neuro-Symbolic Architecture

The explainability of instructional decisions is also preserved at this layer. In other words, each educational recommendation or intervention can be justified based on the conceptual relationships represented in the knowledge graph and the semantic rules used during inference [16]. For example, a recommendation for an educational resource may be accompanied by an explanation such as: “This resource is recommended because a weakness has been identified in Concept X, which serves as a prerequisite for Concept Y.” This capability can enhance the transparency and trustworthiness of the system in its interactions with learners and instructors.

The generated instructional actions are delivered to users through the digital learning environment or Intelligent Tutoring System. The interactions resulting from these actions generate new data concerning learner behavior and performance, which can be used in subsequent cycles of analysis and modeling. In this way, the adaptability cycle of the system is completed. As illustrated in Figure 2, the data flow begins in the Data and Interaction Layer and, after passing through semantic processing, representation, reasoning, and decision-making stages, is ultimately transformed into an adaptive instructional action in Layer 5.

3.7. Innovation of the Proposed Architecture

The primary innovation of the proposed architecture lies in the feedback-oriented integration of data-driven analytics and symbolic reasoning around a knowledge graph-based semantic model [10, 15]. Rather than proposing a specific algorithm, this conceptual framework provides an architecture in which data-driven analytical methods and symbolic structures interact with one another to facilitate the continuous updating of the learner model.

Unlike purely symbolic approaches, which face limitations in extracting behavioral patterns from learner interaction data [1, 2, 5, 9], and purely data-driven approaches, which generally lack explicit semantic representation and sufficient explainability [4, 7, 11, 13], the proposed architecture distinguishes between the roles of “representation” and “updating” across Layers 3 and 4. By establishing a mechanism for bidirectional interaction between the analytical and symbolic components, the architecture enables dynamic learner-model updating, knowledge-based reasoning, and the generation of explainable instructional recommendations within a unified layered framework.

In contrast to the cascading approaches commonly employed in previous studies [4], in which data-driven and symbolic components operate sequentially without feedback, the interaction between data-driven analytics and symbolic reasoning in the proposed architecture is designed such that the output of each component can contribute to improving the operation of the other [14]. This bidirectional interaction allows the learner model to evolve based on newly identified behavioral evidence while enabling semantic knowledge and domain rules to contribute to the interpretation and validation of analytical results.

Another distinguishing feature of the proposed architecture is its emphasis on explainability across all layers, particularly Layers 4 and 5. This characteristic differentiates the proposed framework from many purely data-driven approaches that operate largely as black-box models and provide limited insight into the rationale underlying their outputs [11, 16]. In the proposed architecture, instructional recommendations are not merely generated from predictive or behavioral patterns; rather, they can be linked to semantic relationships, domain rules, learner-state representations, and inferred prerequisite relationships within the knowledge graph. Consequently, the system can potentially provide a meaningful explanation for why a particular instructional action has been recommended.

Although the proposed architecture is conceptual at this stage, it provides a structured foundation for developing Intelligent Tutoring Systems capable of simultaneously benefiting from the accuracy and flexibility of data-driven methods and the transparency and interpretability of symbolic approaches [10, 15]. The architecture is therefore intended as a technology-independent conceptual framework rather than as a specification of a single machine learning or reasoning algorithm.

As illustrated in Figure 1, the proposed architecture consists of five layers that collectively represent the flow of information from the Data and Interaction Layer to the Adaptive Instructional Action Layer. This layered organization separates data acquisition, semantic knowledge representation, learner modeling, neuro-symbolic analysis and reasoning, and pedagogical decision-making while maintaining feedback connections among the relevant components.

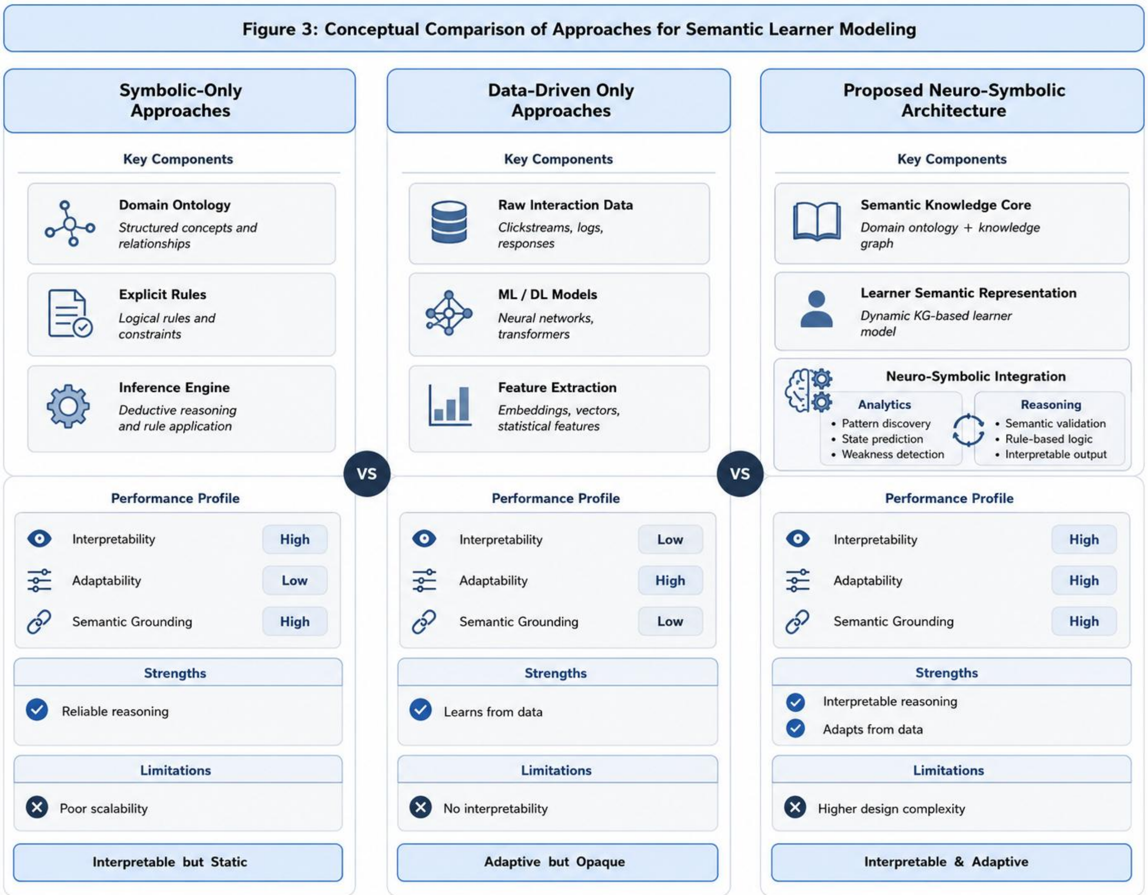

Fig. 3. Conceptual Comparison of Symbolic, Data-Driven, and Neuro-Symbolic Approaches to Learner Modeling

4. DISCUSSION

As demonstrated in the literature review presented in Section 2, research on semantic learner modeling in Intelligent Tutoring Systems can generally be classified into three major streams: ontology- and Semantic Web-based approaches [1, 2, 5], knowledge graph-based approaches and semantic recommender systems [3, 4, 7], and data-driven and hybrid approaches [4, 7]. Each of these research streams has made important contributions to the advancement of learner modeling; however, they also face limitations, particularly with respect to integrating semantic knowledge representation with the analysis of learner interaction data in digital learning environments.

As conceptually illustrated in Figure 3, purely symbolic approaches (e.g., [1, 9, 12]) and purely data-driven approaches (e.g., [4, 7, 11]), despite their respective strengths, face significant limitations in terms of flexibility or interpretability. In contrast, the architecture proposed in this study adopts a neuro-symbolic approach, consistent with recent research [10, 15, 17], to establish a balance between these two dimensions.

Recent studies have independently investigated the development of neuro-symbolic architectures for educational applications. Examples include the NSCR framework for classroom analysis [17], the hybrid CIFNet architecture for instructional decision-making [18], and the knowledge graph-based GraphMASAL adaptive system [19]. Consistent with the architectural approach proposed in this paper, these studies emphasize the integration of data-driven analysis with symbolic reasoning and transparent learner modeling.

The conceptual architecture proposed in this study seeks to integrate these research directions within a unified structure through a layered, knowledge graph-based neuro-symbolic framework. In this framework, knowledge graphs and ontologies serve as the underlying infrastructure for representing domain knowledge and the learner model, while learner-interaction data analytics enables the extraction of behavioral patterns and dynamic updating of the learner's semantic model. The combination of these two approaches enables the simultaneous exploitation of the representation and reasoning capabilities of symbolic methods and the analytical capabilities of data-driven methods.

The following sections examine the relationship between the proposed architecture and the major research streams in learner modeling and discuss its conceptual contributions in comparison with previous approaches.

4.1. Relationship with Ontology- and Semantic Web-Based Approaches

Research based on ontologies and Semantic Web technologies has played an important role in the development of semantic models for educational applications. Studies reported in [1] and [2] demonstrate that technologies such as RDF, OWL, and ontology-based reasoning mechanisms can support learner modeling, adaptive learning, competency assessment, and educational recommender systems through explicit and structured knowledge representation. These approaches enable educational concepts, relationships among them, learner characteristics, and instructional rules to be represented in a machine-interpretable format and consequently facilitate knowledge-based reasoning, conceptual consistency checking, and explainable decision-making.

However, as discussed in Section 2.1, many ontology-based systems rely heavily on predefined conceptual structures and manually designed rules. This dependency can create limitations in digital learning environments where learner interaction data are continuously generated at large scale. In particular, identifying implicit behavioral patterns or learning trends that are not explicitly modeled within the ontology can be challenging for such approaches.

The architecture proposed in this study seeks to mitigate this limitation by incorporating a data-driven analytics component into the Neuro-Symbolic Integration and Reasoning Layer (Layer 4). Within this framework, data-driven methods are employed to extract learning patterns and indicators from learner interaction data, and the resulting outputs are used as complementary evidence alongside semantic representations. At the same time, ontologies and knowledge graphs in the Semantic Knowledge Core (Layer 2) remain the structural reference for representing domain knowledge and the learner model.

Outputs generated by the data-driven component can contribute to updating the semantic learner model in the Semantic Learner Representation Layer (Layer 3), while the symbolic reasoning component uses the existing semantic structures to interpret these results and, where necessary, refine them within the context of domain knowledge. In this manner, the proposed architecture seeks to establish a balance between the advantages of explicit knowledge representation offered by ontology-based approaches and the ability to extract behavioral patterns from learner interaction data.

Overall, this approach can serve as a bridge between explicit knowledge representations in Semantic Web technologies and learning-data analytics in digital environments, providing a foundation for developing learner models that are more flexible while retaining interpretability.

4.2. Relationship with Knowledge Graph-Based Approaches and Semantic Recommender Systems

Another group of studies related to learner modeling focuses on the use of knowledge graphs and semantic recommendation mechanisms to enrich educational knowledge representation and improve the accuracy of instructional recommendations. Studies such as [3], [4], and [7] have shown that employing semantic knowledge resources, including knowledge graphs such as DBpedia and ConceptNet, can improve the recommendation of learning resources by identifying conceptual relationships among educational topics and concepts.

In these approaches, knowledge graphs are generally used to model educational concepts, relationships among them, and semantic connections between learning resources, thereby facilitating the retrieval and matching of content with learner needs. As also noted in review [8], learner-model ontologies and educational-content ontologies provide valuable foundations for knowledge-based recommender systems in e-learning and enable content personalization according to individual differences among learners.

Despite these advantages, an examination of studies in this area indicates that their primary focus has often been on enriching content representation and improving educational-resource recommendation mechanisms, while the learner model plays a relatively limited role in the overall system structure. In many cases, learner characteristics are represented as a simple profile or a set of input parameters rather than being modeled as part of a dynamic and integrated semantic structure within the knowledge graph. Consequently, the interaction between learner behavioral-data analysis and semantic knowledge representation is often limited to specific stages of the recommendation process, and an explicit mechanism for continuously updating the semantic learner model within the knowledge graph framework is not generally provided.

The architecture proposed in this study seeks to reduce this gap by treating the semantic learner model as an integrated component of the knowledge graph structure. Within this framework, the learner model is not merely considered an input profile; rather, it is conceptualized as a dynamic semantic structure that is updated using learner interaction data through the feedback-oriented integration mechanism in the Neuro-Symbolic Integration and Reasoning Layer (Layer 4).

This design enables a direct connection between behavioral-data analysis and semantic learner representation and provides a foundation for more precise reasoning and the generation of interpretable instructional recommendations. Accordingly, the proposed architecture can contribute to narrowing the gap between knowledge graph-based recommender approaches and dynamic semantic learner modeling.

4.3. Relationship with Data-Driven and Hybrid Approaches

The third major stream of research related to learner modeling focuses on the use of data-driven methods, machine learning, and deep learning to analyze learner behavior and extract interaction patterns. Studies such as [4], [7], [11], and [13] have demonstrated that data-driven methods can effectively identify latent behavioral patterns, predict learning states, and detect educational needs. In particular, the use of deep learning models such as Long Short-Term Memory (LSTM) in combination with semantic knowledge resources [4] has demonstrated the potential to improve the accuracy of educational-resource recommendation by exploiting learner interaction data.

Despite these achievements, data-driven approaches face important challenges regarding interpretability and semantic transparency. In many cases, outputs produced by data-driven models are represented as feature vectors, statistical parameters, or numerical predictions that do not have an explicit connection to the conceptual structure of the educational domain. This makes it difficult for instructors and learners to understand the rationale behind recommendations or instructional decisions and may reduce confidence in the system.

Furthermore, in many existing hybrid approaches, the role of symbolic components is often limited to the initial stages of the process, such as data enrichment, preprocessing, or content representation, without establishing a deeper integration between behavioral-data analysis and semantic knowledge representation [4].

The architecture proposed in this study seeks to address this limitation through a feedback-oriented integration mechanism within the Neuro-Symbolic Integration and Reasoning Layer (Layer 4). In this framework, data-driven methods are used to extract behavioral patterns from learner interactions; however, their outputs are not used directly as the basis for instructional decisions. Instead, they serve as evidence for updating the semantic learner model within the knowledge graph.

The symbolic reasoning component then uses ontologies, semantic rules, and conceptual relationships to interpret these evidential outputs and generate interpretable results. Accordingly, the interaction between data-driven analytics and symbolic reasoning is designed as an integrated process in which the outputs of each component can contribute to the interpretation and updating of the other component.

This design enables the proposed architecture to benefit from the accuracy and flexibility of data-driven methods in extracting behavioral patterns, while maintaining the interpretability and transparency required for educational applications through the semantic structures represented in the knowledge graph.

The emphasis on explainability in Layers 4 and 5 further distinguishes the proposed architecture from many purely data-driven approaches that predominantly operate as black-box models. Consequently, the proposed architecture can be regarded as a conceptual step toward developing Intelligent Tutoring Systems that combine the analytical power of learner-interaction data with the transparency of semantic knowledge representation.

4.4. Contributions of the Proposed Architecture

Based on the analyses presented in Sections 4.1–4.3, the proposed architecture makes several conceptual contributions in comparison with the three main research streams in semantic learner modeling: ontology-based approaches, knowledge-graph-based approaches and semantic recommender systems, and data-driven and hybrid approaches.

The first contribution lies in the layered organization and explicit separation of responsibilities throughout the learner-modeling process. The architecture is designed as a five-layer structure in which each layer has a clearly defined role. The Data and Interaction Layer is responsible for collecting and managing learner interaction data, while the Semantic Knowledge Core provides the necessary infrastructure for representing educational concepts and their relationships. Subsequently, the Semantic Learner Representation Layer maintains the dynamic learner model in semantic structures. The Neuro-Symbolic Integration and Reasoning Layer combines data analytics with knowledge-based reasoning, while the Adaptive Instructional Action Layer ultimately transforms the resulting outputs into educational decisions and interventions. This layered separation enhances architectural transparency and enables individual components to be developed or improved without disrupting other parts of the system. Compared with some existing hybrid approaches in which the boundaries between data analytics and semantic reasoning are not fully defined [4], the proposed architecture explicitly specifies the role of each component.

The second contribution is the emphasis on the centrality of the semantic learner model within the knowledge graph. In many knowledge-graph-based approaches, the learner model is often treated as a simple profile or set of input parameters rather than being modeled as a dynamic component of the knowledge structure [3, 7]. In contrast, the proposed architecture treats the semantic learner model as an integrated component of the knowledge graph and continuously updates it in the Semantic Learner Representation Layer based on interaction data. This approach enables a direct connection between behavioral data analytics and conceptual knowledge representation, thereby creating the basis for more accurate and interpretable educational inferences.

Another important contribution is the emphasis on explainability in educational decision-making. One of the fundamental challenges of data-driven approaches in educational systems is the limited interpretability of their outputs and the difficulty of explaining the rationale underlying generated decisions [4, 7]. In the proposed architecture, explainability is treated as an inherent design property of the reasoning and instructional-action layers. The symbolic reasoning component can generate interpretable results using ontologies, semantic rules, and relationships within the knowledge graph [16], while the Adaptive Instructional Action Layer can justify instructional recommendations or interventions by referring to conceptual relationships represented in the knowledge graph. This feature distinguishes the proposed architecture from many purely data-driven approaches that typically operate as opaque models.

Finally, the proposed architecture offers a considerable degree of flexibility and modularity in its design. Its layered structure enables individual components to be developed independently or replaced with alternative methods. For example, the methods employed by the data-driven analytics component can be updated without modifying the other layers, while the ontologies within the Semantic Knowledge Core can be expanded according to the requirements of different educational domains. Furthermore, the proposed architecture is not dependent on a specific algorithm for data analytics and can employ statistical methods, machine learning, or deep learning [4, 7] without requiring changes to its overall structure.

Overall, these characteristics indicate that the proposed architecture, by leveraging the strengths of existing approaches while attempting to mitigate their limitations, provides a conceptual framework for developing Intelligent Tutoring Systems that combine the analytical capabilities of data-driven methods with the transparency and interpretability of semantic representations. From this perspective, the proposed architecture can be regarded as a conceptual step toward the convergence of symbolic and data-driven approaches in learner modeling, although empirical validation remains necessary.

4.5. Limitations

Despite the conceptual contributions discussed above, the proposed architecture has several fundamental limitations that should be considered.

First and most importantly, the architecture is presented at a conceptual level, and neither implementation nor empirical validation was conducted in this study. The proposed architecture constitutes a conceptual framework, while empirical evaluation, practical implementation, and comparison with existing approaches are proposed as directions for future research. Therefore, any claims concerning the effectiveness or superiority of this architecture over existing approaches remain hypotheses until supported by implementation and empirical evaluation.

The second limitation concerns the architecture's dependence on the availability of rich and well-structured ontologies and knowledge graphs. The development, maintenance, and updating of such semantic resources require considerable effort, domain expertise, and time [1, 5]. In dynamic educational environments where concepts and content change rapidly, maintaining these knowledge structures in an up-to-date state can be challenging. Furthermore, the quality of ontologies and knowledge graphs will directly affect the performance of higher layers, particularly the reasoning and learner-representation layers.

The third limitation concerns the data-driven analytics component. Although the proposed architecture is independent of any specific algorithm, this characteristic does not eliminate the need to select appropriate analytical methods. Practical implementation of this component requires careful selection of statistical, machine-learning, or deep-learning methods based on data characteristics, available computational resources, and educational objectives. The overall performance of the system will depend substantially on these choices.

The fourth limitation concerns the scalability of the architecture in large-scale learning environments. In scenarios involving large numbers of concurrent learners, continuous updating of semantic models in the knowledge graph and execution of symbolic reasoning processes may create computational challenges and performance overhead [6, 7]. At this stage, the proposed architecture does not provide a specific solution for managing these challenges.

Finally, the conceptual nature of the architecture and the absence of implementation details for certain components such as the precise mechanism for mapping data-driven outputs to semantic assertions in the knowledge graph indicate that additional technical and empirical studies are required for practical implementation of the framework.

4.6. Implications for Future Research

The limitations identified in this study suggest several important directions for future research. The first and most important step is the implementation and empirical validation of the proposed architecture in real educational environments. Future studies could use learner interaction data from systems such as Learning Management Systems or online learning environments to implement a practical instance of the architecture and evaluate its performance in terms of learner-modeling accuracy, quality of instructional recommendations, explainability of results, and impact on the learning process. Such studies could employ standard evaluation metrics used in recommender systems and predictive models, such as precision, recall, and F1-score, to assess performance.

Another important research direction is the development of semi-automated or automated methods for constructing and updating ontologies and knowledge graphs. Given the cost and complexity of ontology engineering in educational environments, future research could focus on ontology-learning methods from educational texts and automated extraction of conceptual relationships to facilitate the development and maintenance of semantic knowledge resources. In addition, future studies could employ hybrid approaches such as KG-RAG to enhance knowledge-graph-based instructional interventions [14].

Furthermore, the proposed framework provides an opportunity to compare and evaluate different data-analytics methods within a common conceptual setting. Future research could investigate the performance of statistical methods, machine learning, and deep learning within this architecture and identify the most appropriate approaches for different educational scenarios. Investigating scalability issues, particularly in large-scale learning environments such as Massive Open Online Courses (MOOCs), and developing effective mechanisms for providing comprehensible explanations to learners and instructors are other important directions for the practical development of this architecture.

5. CONCLUSION

This study addressed existing gaps in learner modeling by proposing a conceptual layered neuro-symbolic architecture based on a knowledge graph. Traditional approaches in this domain either face limitations in interpretability and ontology-based representation, as in symbolic methods, or lack semantic transparency when dealing with the complexity of behavioral data, as in data-driven methods. Through a five-layer integration, the proposed architecture establishes an effective connection between logical inference (symbolic) and behavioral patterns (neural/data-driven), resulting in a system characterized by high explainability and dynamic adaptability.

The primary innovation of this work is the design of a feedback-oriented mechanism centered on a knowledge-graph-based semantic model. In addition to improving the accuracy of learner modeling, this mechanism enables semantic reasoning alongside predictive analytics. As a conceptual framework, the proposed architecture provides an appropriate foundation for moving beyond "black-box" approaches in Intelligent Tutoring Systems and enables instructors and educational systems to understand the basis of instructional inferences transparently.

Finally, given that the present architecture is proposed at a conceptual level and empirical evaluation is identified as a direction for future research, this study establishes a clear pathway for experimental implementation in real-world environments. Although no specific neural model has been employed at this stage, the architecture is designed to accommodate different types of data-driven components, including neural networks, thereby increasing its adaptability to diverse educational scenarios. Developing automated ontology-extraction methods and validating the scalability of the model in online learning environments are essential steps toward maturing this approach for practical and industrial applications. Overall, the convergence of symbolic artificial intelligence and machine learning within a knowledge-graph framework represents a strategic approach for the next generation of explainable Intelligent Tutoring Systems.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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