Ontology for Educational Recommendation System in an Immersive Environment

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Abstract. *Educational Recommendation Systems (ERS) face challenges in evaluating student behavior and performance, aiming to generate personalized learning suggestions. This paper proposes an ontology designed to support ERS in immersive learning environments. The ontology models key elements such as student interactions, learning materials, and competencies. As part of the validation process, an automatic script was developed to generate ontology instances, and SPARQL queries were executed to simulate interaction scenarios. The results include the defined ontology taxonomy and a demonstration of how its structure can represent adaptive learning contexts.*

1. Introduction

Adaptive learning is an educational approach that utilizes technology to provide personalized learning experiences tailored to individual students' needs, preferences, and progress. It leverages data-driven algorithms and artificial intelligence to dynamically adjust the content, the delivery, and the pace of instruction based on learners' performance and engagement. By adapting to the specific requirements of each student, adaptive learning promotes effective and efficient learning, maximizes engagement, and enhances educational outcomes [Gligorea et al. 2023]. Recommendation systems (RS) are technological resources that offer item suggestions to support users in different choice processes, such as deciding what to buy, what music to listen to or what news to read [Ricci et al. 2022]. The use of RS in educational environments can bring benefits to various tasks related to the teaching and learning process, such as filtering the large amount of educational information to make relevant recommendations to students, making the virtual environment an adaptive learning system, adapting to preferences, goals and learning style. The work [Rawat and Dwivedi 2017], for example, proposes a courses recommendation system to students based on their profiles, that is, courses with styles based on students' behaviors.

According to [Hey et al. 2009] as cited in [Peng et al. 2019], the rise of personalized adaptive learning is driven by big data technologies, which continuously generate vast and diverse datasets. Data is thus a crucial part of a recommendation system for adaptive learning [Sin et al. 2023]. The data collection can be carried out explicitly or implicitly [Bobadilla et al. 2013, Park et al. 2012], where these data reflect the behavior and help the classification of user profiles, thus assisting the recommendation tasks.

Ontologies play a crucial role in knowledge management and representation by formally modeling the structure of a system - its relevant entities, attributes, and relationships - based on its conceptualization [Staab and Studer 2009]. According to [Gruber 1995], an ontology is defined as a formal and explicit specification of a shared conceptualization. It provides a hierarchical organization of concepts with associated properties and relations [Stancin et al. 2020], enabling reasoning, analysis, knowledge sharing, and reuse. Ontologies are widely used across scientific domains and are particularly relevant in e-learning, where they support the representation of domain knowledge, personalized recommendation of content, curriculum design, and assessment of learning processes [Stancin et al. 2020].

The present work proposes an ontology-based data model to support an Educational Recommendation System (ERS) within an immersive adaptive learning environment. The ontology is described using the OWL (Web Ontology Language) language, formalizing entities through concepts, relationships, and instances that represent the domain. As students interact with elements in the immersive environment, these interactions are recorded in the ontology, enabling the extraction of relevant data for the ERS, which then generates personalized learning recommendations. The data model also serves as the foundation for constructing a knowledge graph schema, defining node types (e.g., students, courses, materials) and relationships (e.g., “access”, “has”, “contains”) between them. Additionally, SPARQL (SPARQL Protocol and RDF Query Language) queries are used to retrieve temporal, semantic, and contextual information, serving as input to the ongoing development of the adaptive recommendation system.

The remainder of this paper is organized as follows: Section 2 reviews the related works. Section 3 presents the formalization of the ontology’s concepts, entities, and relationships. Section 4 discusses the main findings. Finally, Section 5 presents the conclusions and future directions.

2. Related Works

Recommendation systems in virtual learning environments have been gaining attention from researchers, partly due to the ease of access and the flexibility they offer in terms of time and location [Silva et al. 2023]. However, [George and Lal 2019] highlights a major challenge in e-learning environments: the overwhelming amount of available information and content, which often prevents students from receiving personalized materials aligned with their individual learning goals.

Immersive learning environments have the potential to enhance student motivation and attention, reduce the burden on teachers and trainers, and compensate for the limitations of conventional teaching methods. They also facilitate institutional understanding of students’ performance, enabling easier identification of individual weaknesses and competencies, which in turn supports personalized learning [Sakr and Abdullah 2024]. To develop effective recommendation tools in immersive contexts, it is essential to consider the application domain and user needs. [Morgado et al. 2022] emphasize the role of recommendation systems in supporting educators by promoting pedagogical activities through technological tools.

The literature review presented in [George and Lal 2019] highlights the effectiveness of ontologies in enhancing recommendation systems. In contrast, approaches that rely solely on machine learning - without the structural support provided by ontologies - often encounter persistent challenges, such as the cold-start problem, data sparsity, and limited recommendation diversity. By formally organizing domain knowledge, ontologies help mitigate these issues and improve the adaptability and precision of recommendation systems.

The ontology enables the construction of a knowledge graph that represents the entities and relationships involved in educational recommendation scenarios within virtual learning environments. This structure captures the semantic context of the data, which is essential for understanding learner behavior and improving the quality of the recommendations. Furthermore, the core idea behind educational recommendation systems in immersive environments is to integrate the semantic richness of knowledge graphs with the engagement potential of virtual reality, thereby enhancing association, exploration, and active learning [Sin et al. 2023].

[Bouihi and Bahaj 2017] emphasize the importance of incorporating the student's context into learning resource recommendations, proposing a three-tier architecture that features a semantic layer composed of three ontologies. Semantic Web technologies such as OWL and SWRL are employed to enable context-aware recommendations. However, the approach is not supported by experimental results or empirical evaluations.

[Tarus et al. 2018] does not present empirical experiments. Instead, it offers a comprehensive review of ontology-based approaches to recommendation systems in the e-learning domain. Although the authors illustrate how ontologies can represent knowledge about students and learning resources, their contribution remains primarily conceptual. The work focuses on categorizing existing techniques and identifying trends in ontology-driven educational recommendations.

While previous studies highlight the potential of recommendation systems to personalize learning in virtual and immersive environments, many - such as [Tarus et al. 2018] and [Bouihi and Bahaj 2017] - focus primarily on conceptual architectures or taxonomies without providing concrete experimental results. In contrast, the present work proposes and implements an ontology specifically designed for immersive educational settings, modeling entities such as students, courses, rooms, materials, and their interactions. Unlike approaches that rely solely on machine learning and often face challenges such as the cold-start problem and data sparsity, this work leverages ontological modeling and semantic relationships to enhance contextual understanding. It also includes validation through automatic instance generation and SPARQL-based simulations of interaction scenarios, demonstrating how the ontology can support adaptive recommendations. By integrating semantic structures with immersive educational environments, this work contributes toward more effective, explainable, and adaptive recommendation systems compared to many general-purpose or non-validated proposals in the literature.

3. Methodology

This section describes the methodology adopted to develop the proposed ontology. The construction followed the Methodology 101 approach [Noy et al. 2001], which encompasses the stages of specification, conceptualization, formalization, and validation. UML diagrams were employed to represent the ontology's classes and relationships. The resulting taxonomy includes key concepts, modeled interactions, and domain constraints. The validation process involved the automatic generation of instances and the execution of SPARQL queries to simulate interaction scenarios and verify the structure's applicability.

3.1. Consider reusing existing ontologies

To strengthen the methodological foundations of this work, key aspects related to ontology reuse and methodological choices were considered. Existing ontologies in the educational domain, particularly those focused on learning recommendation, were analyzed to assess their potential for reuse. However, as discussed in Section 2, most of these ontologies either lacked alignment with immersive environments or failed to explicitly model adaptive interaction data, thereby limiting their applicability in this context. The proposed ontology addresses these gaps by incorporating interaction patterns and contextual elements often absent from general-purpose educational ontologies, thus offering greater semantic precision and adaptability.

3.2. Taxonomy

To provide a clear and logical structure for organizing the storage and retrieval of information in an ontology, it is essential to identify its entities along with their object and data properties. Object properties represent interaction relationships between entities, while data properties define the intrinsic characteristics of each instance derived from those entities. The "Material" and "Question" entities do not have object properties, as they do not initiate interactions with other entities; instead, they serve as targets of interactions, that is, they are only "interacted with". The ontology includes the following entities: Student, Course, Room, Material, Question, and Interaction.

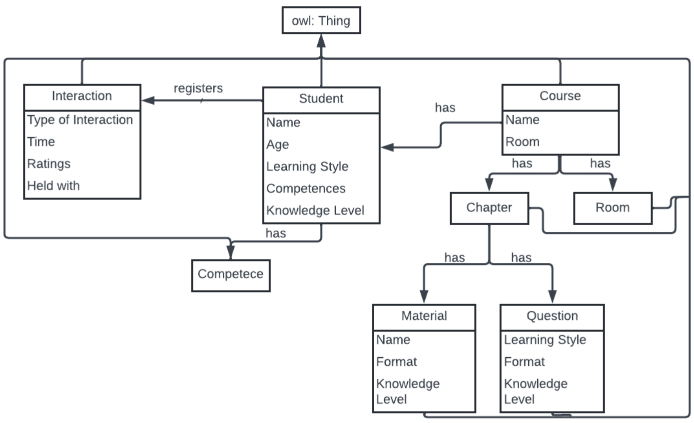

Figure 1. Ontology - Classes and Properties

The ontology encompasses classes, properties, and instances related to an adaptive learning system in an immersive environment (Figure 1). Classes represent groups of entities with shared characteristics, such as “Student”, “Room”, and “Educational Resource”. Properties define relationships between classes, which may be hierarchical, such as a “is a” relationship (e.g. “Classroom” is a subclass of “Room”), domain-specific, such as “participates in” (e.g. “Student” participates in “Python Class”). Instances refer to specific individuals that belong to a given class; for example, a student named “John” would be an instance of the class “Student”.

Table 1 presents a formal representation of the ontology by specifying its constraints using the subject–predicate–object triple format. It illustrates access relationships by defining which entities (e.g., students) interact with specific resources within the immersive environment.

Subject	Predicate	Object		Subject	Predicate	Object
Student	Accesses	Room		Student	Accesses	Course
Student	Accesses	Material		Student	Accesses	Question
Student	Has	Competence		Student	Has	Level
Student	Has	Learning Style		Student	Has	Name
Student	Has	Id		Student	Generates	Interaction
Room	Contains	Course		Course	Contains	Id
Course	Contains	Level		Material	Contains	Level
Material	Contains	Ratings		Questions	Contain	Level
Questions	Contain	Ratings		Interaction	Has	Id
Interaction	Registers	Interacted Object				

Table 1. Constraints of the Ontology

3.2.1. Student

The *Student* entity represents the learner who interacts with various components of the immersive environment, including peers, courses, and resources. These interactions, captured via the *Interaction* entity, serve as input for personalized recommendations. Student data properties include demographic attributes, knowledge level (beginner to advanced), learning style based on the Felder–Silverman Model [Felder and Silverman 1988], and prior competences. Behavioral data from the environment, such as room access, material usage, and peer interactions, contribute to the student’s recommendation profile.

3.2.2. Course

The *Course* entity refers to the learning units offered to students through the immersive learning system. In the context of adaptive learning, the system is expected to provide personalized recommendations on course-related materials and questions. Each course is composed of chapters, which in turn are divided into tracks that contain the instructional materials. Additionally, a course is associated with a physical or virtual room where it is conducted, such as a classroom or a laboratory. The object properties associated with *Course* include the relationship *Contain Material*, indicating that each course provides learning materials to enrolled students, and *Contain Questions*, which refers to the set of questions associated with the course that students are expected to answer. The main data property of a course is its level of knowledge, which characterizes the complexity or depth of the course content - typically classified as beginner, intermediate, or advanced -

and can be used as a parameter in the recommendation process.

3.2.3. Room

The *Room* entity represents a physical or virtual environment in which learning activities take place, such as a classroom, library, laboratory, or living room. Each room contains resources that students can access and interact with. For instance, a library may provide access to books, a classroom may include a whiteboard, a laboratory may offer equipment, and a living room may serve as a collaborative space where students interact with one another. Multiple interactions can be recorded within each room, reflecting various forms of student engagement. The main object property associated with *Room* is *Belongs to a Course*, indicating that a room is linked to a specific course, which enables its availability within the immersive learning environment. Regarding data properties, a room has a *Name*, used as an identifier to distinguish it from other learning spaces.

3.2.4. Material

The *Material* entity refers to learning resources associated with a course that can be accessed and evaluated by students. These materials may take the form of a book, video, podcast, or even a question. They can also be recommended by the system based on the student's profile and learning preferences. As previously mentioned, the *Material* entity does not have object properties, as it does not initiate interactions with other entities in the ontology; it only serves as a target of interactions. The data properties associated with *Material* include its *Name*, which identifies the resource; its *Level*, indicating the complexity (beginner, intermediate, or advanced); its *Style*, defined according to the FSLSM (Felder–Silverman Learning Style Model) dimensions—perception, input, organization, processing, and understanding; and its *Format*, which specifies the type of resource (Material format), such as book, video, or podcast.

3.2.5. Questions

The *Question* entity represents assessment items associated with a course that can be answered and evaluated by students. Questions may take various formats, including discursive, objective (multiple choice), or true/false. These elements can also be recommended to students by the system, based on their learning profile and interaction history. As previously mentioned, the *Question* entity does not have object properties, as it does not initiate interactions with other entities—it serves solely as a target of interaction. The data properties of a *Question* include an *Id*, which uniquely identifies each question; a *Level*, representing the question's difficulty (beginner, intermediate, or advanced); a *Style*, which aligns with the FSLSM (Felder–Silverman Learning Style Model) dimensions—perception, input, organization, processing, and understanding; and a *Format*, indicating the type of question, such as discursive, objective, or true/false.

3.3. Interaction

The *Interaction* entity represents student behavior within the immersive environment. These interactions are fundamental for identifying individual preferences and enabling personalized recommendations. The *Student* entity must be capable of instantiating interactions, which are registered as part of the ontology.

The object property associated with *Interaction* is *Perform Interaction*, which links a student to the entity involved in the interaction - such as a *Material* or a *Ques-*

tion. The data properties of an *Interaction* include an *Id*, which uniquely identifies each interaction; *Time*, indicating when the interaction occurred; *Evaluation*, which represents a feedback score generated when interacting with materials or answering questions; and *Type*, specifying the nature of the interaction (e.g., enter, exit, chat, reply, among others).

3.4. Constraints

In an ontology, constraints are defined as conditions or rules imposed on elements or concepts to ensure that the data represented remain consistent and semantically valid. These constraints play a critical role in guiding the logical structure of the ontology and preventing invalid or incoherent relationships. In the proposed ontology, the main constraints are associated with the actions permitted to students, reflecting the scope of the immersive environment for adaptive learning. Access to resources within the environment depends on the student's interactions. Each student can perform multiple interactions, and each interaction is directly linked to a specific object that receives the action.

Within this context, several constraints govern access and evaluation logic: to access a course, the student must first enter a room where the course is offered; to access a material, the student must interact with it, and the material must be associated with the corresponding course; to evaluate a material, the student must have previously accessed it. These restrictions ensure the logical flow of student activity and maintain the consistency of the learning process modeled by the ontology.

3.5. Automatic generator

The validation of the proposed ontology required the construction of a knowledge base containing a significant volume of instances that represent realistic scenarios within the immersive educational environment. However, as the system is still under development, one of the main challenges faced in this study was the lack of a real-world dataset with the necessary characteristics. To address this limitation, an automatic instance generator was implemented in Python. The tool was designed to create a large and diverse set of ontology instances in a randomized and automated manner. The generation process took into account the classes, properties, interactions, constraints, and relationships defined in the model, ensuring that the resulting knowledge base was representative and coherent for validation purposes.

The generator was employed to automatically create instances for all entities defined in the ontology, including *Student*, *Material*, *Course*, *Room*, and *Question*. In addition to populating these classes, it also generated instances of the modeled relationships, such as interactions between students and materials, and peer-to-peer interactions between students. For the creation of entities—unlike the generation of interaction instances—it was necessary to define predefined tables containing possible attribute values. These included generic names for students and courses, identifiers for rooms, formats for materials (e.g., audio, video, simulation), and types of questions (e.g., essay, multiple choice, true/false). This approach ensured diversity and realism in the generated knowledge base, while adhering to the structural and semantic constraints of the ontology.

4. Results

To validate the proposed ontology, this section presents preliminary results based on its application. The validation is structured in two parts. The first part focuses on assessing the effectiveness of the automatic instance generator, which was designed to populate the ontology by generating instances that adhere to its structural definitions and constraints. In the second part, SPARQL queries are executed over the generated knowledge base to simulate and explore illustrative scenarios of interaction within the immersive educational environment. These queries aim to demonstrate the ontology's ability to support semantic retrieval of contextual and behavioral information, which is essential for adaptive educational recommendations.

4.1. Validation of the Automatic Generator

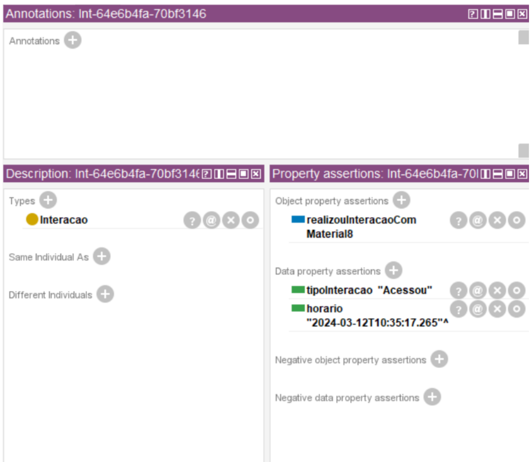

Figure 2. Interaction manually created

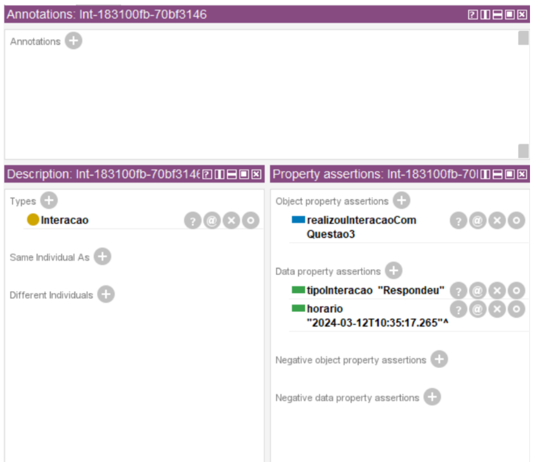

Figure 3. Interaction automatically created by the generator

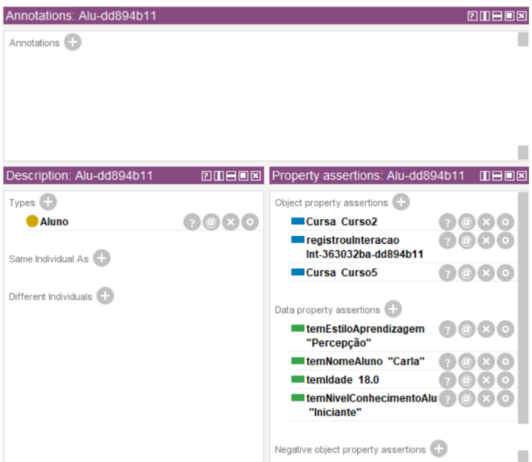

Figure 4. Student manually created

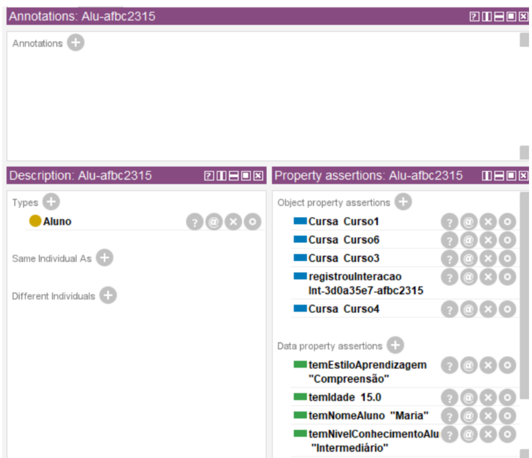

Figure 5. Student automatically created by the generator

The proposed ontology was developed using the Protégé tool [Musen 2015], and a Python script was created to load the ontology in `.owl` format and generate instances programmatically. To verify the script's functionality, a comparison was made between manually created and automatically generated instances. As illustrated in Figures 2 to 5, both types of instances preserve structural consistency, such as interactions between students and learning objects over time.

In another illustrative example of the use of the automatic generator, Figure 4 displays a student instance created manually. This student, named Carla, is 18 years old, has a beginner level of knowledge, a learning style categorized as perception, and has performed three interactions. Figure 5 presents a similar student instance generated automatically by the script. The student, named Maria, is 15 years old, has an intermediate level of knowledge, a learning style classified as comprehension, and has performed five interactions. This comparison reinforces the script's ability to create realistic and structurally consistent instances aligned with those created manually in Protégé.

4.2. Model Validation with SPARQL Queries

To verify the internal consistency and semantic coherence of the knowledge graph, a set of queries was executed over the data generated from the proposed ontology. The SPARQL language (*Simple Protocol and RDF Query Language*) was used to create the queries. This is a query language standardized by the World Wide Web Consortium (W3C) to retrieve data stored in RDF format (*Resource Description Framework*), used to represent information/knowledge of a domain.

4.2.1. Scenarios

Two scenarios were defined to guide the SPARQL queries, each representing a path in the knowledge graph. In the first, a student enrolls in a course and accesses various rooms (e.g., classroom, library), interacting with peers and resources, and these actions are systematically recorded in the ontology. In the second, the student engages with learning materials and questions, generating a history of accesses and evaluations used to support personalized recommendations, as presented below.

4.2.2. SPARQL queries

Figure 6 presents a SPARQL query designed to extract a student's interaction history, as described in the first validation scenario. This scenario reflects the types of interactions a student may perform within the adaptive learning system in an immersive environment. As discussed in Section 3.3, interactions are modeled as instances of the *Interaction* class, with each action recorded explicitly in the ontology.

Figures 7, 8, and 9 illustrate SPARQL queries aimed at generating personalized recommendations based on the student's behavioral patterns. By analyzing Figure 7, it is possible to observe that the student under analysis has interacted predominantly with other students classified as having a "beginner" knowledge level. This behavior may indicate that the student's own level is also beginner. Based on this assumption, the recommendation system should prioritize materials suitable for this level of knowledge. Figures 8 and 9 present queries that retrieve learning materials and questions accessed by students identified as beginners. These resources are likely to be relevant to learners at the same level and can therefore be considered as potential recommendations for the student in question.

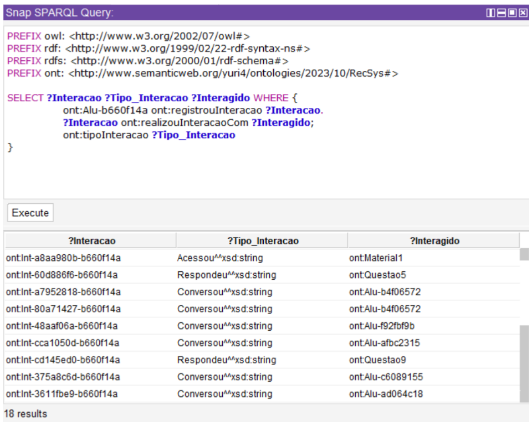

Figure 6. Student history query

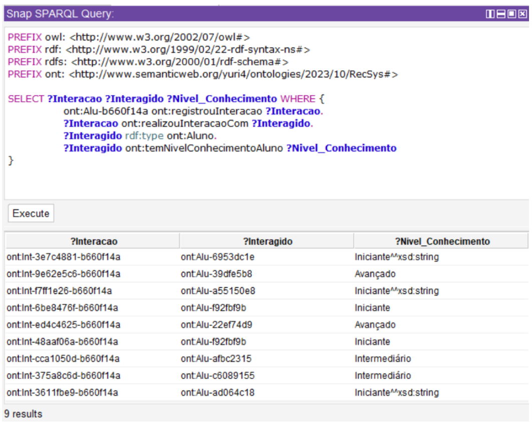

Figure 7. Students interactions query

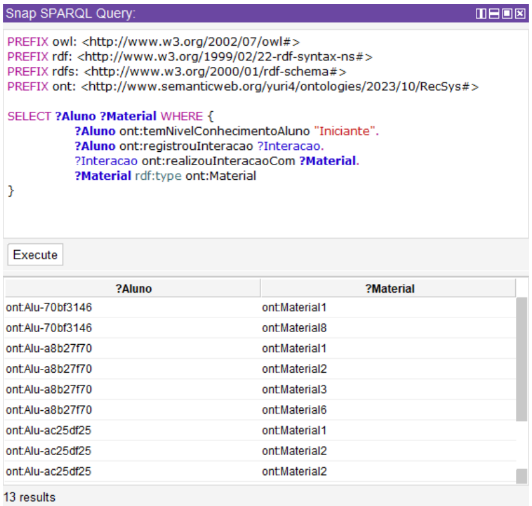

Figure 8. Query about materials accessed by the students with “beginner” level

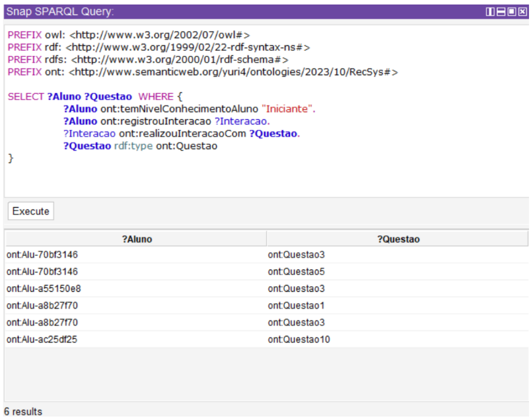

Figure 9. Query about questions accessed by students with “beginner” level

The proposed ontology offers significant contributions, particularly the standardization of terms and concepts that promote interoperability between systems and improve the organization and retrieval of information essential to the recommendation process. Among the main results achieved is the validation of the ontology through illustrative scenarios, which demonstrated its capacity to support personalized recommendations in immersive learning environments. The ontology also enables the modeling of frequency and temporality in user–artifact interactions, which are critical for enhancing the personalization of learning experiences within adaptive educational systems.

4.3. Limitations

The proposed ontology models key elements of an immersive educational environment but faces challenges in formally defining and measuring attributes such as learning style and interaction level, which may require external data or advanced metrics, such as frequency, duration, and semantic relevance. It supports learning material recommendations by linking students to resources through contextual relationships. To validate its structure, SPARQL queries were used to retrieve meaningful interaction patterns. Although formal consistency checking with reasoners was not the focus, the ontology was designed to conform to the OWL DL (Description Logic) profile, avoiding constructs that compromise decidability, such as metaclasses and property punning. This work constitutes an initial step toward the development of ontology-based recommendation systems, emphasizing semantic modeling as a foundation for future adaptive educational applications.

5. Conclusions and Future Work

Educational recommendation systems face challenges in evaluating student performance and providing personalized suggestions [Silva et al. 2023]. This work proposes an ontology for immersive educational environments to formalize entity interactions and support recommendation processes based on personalized item characteristics. The ontology includes concepts, relationships, and constraints involving entities such as Student, Course, Room, Material, and Interaction. Experiments using SPARQL queries simulated student interactions and demonstrated their potential to inform adaptive recommendations.

Future work includes applying the automatic instance generator to expand new interaction scenarios within the immersive educational environment, and exploring additional SPARQL queries to enhance the capabilities of the educational recommendation system - especially by incorporating new pedagogical and didactic aspects into the recommendations. Additionally, it is intended to incorporate SWRL rules to enable more expressive inferencing capabilities, such as defining rules for implicit student preferences or prerequisite relationships between learning objects.

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