

OntoLearn: A Formal Ontology for Competency-Based Learning Analytics and Semantic Modeling

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Abstract. *Competency-Based Learning (CBL) often lacks the semantic granularity required for advanced Learning Analytics. We present OntoLearn, an OWL 2 DL ontology for modeling Knowledge, Skills, and Attitudes (KSA). Developed via a hybrid agile methodology (Ontology 101 + SAMOD), the model employs complex axioms to infer proficiency levels and prerequisites. Validation follows a hybrid framework: structural auditing with OOPS!, consistency checking with HermiT, and functional testing via Generative AI (Gemini 3) in a human-in-the-loop paradigm. A case study with synthetic data confirms 100% logical consistency and full functional coverage of eight competency questions after an iterative refinement cycle, with axioms rated 4.8/5 for semantic plausibility.*

Resumo. *A implementação do Ensino Baseado em Competências (EBC) carece de granularidade semântica para Learning Analytics. Apresentamos a OntoLearn, uma ontologia OWL 2 DL para modelar a tríade CHA (Conhecimentos, Habilidades e Atitudes). O desenvolvimento integra a metodologia 101 ao framework ágil SAMOD. A validação utiliza uma abordagem híbrida: auditoria estrutural com OOPS!, checagem de consistência com HermiT e testes funcionais via IA Generativa (Gemini 3) sob o paradigma human-in-the-loop. Um estudo de caso com dados sintéticos confirma 100% de consistência lógica e cobertura funcional plena das oito perguntas de competência após um ciclo iterativo de refinamento, com axiomas avaliados em 4.8/5 quanto à plausibilidade semântica.*

1. Introduction

The evolution of education in the 21st century is marked by a significant shift from content-centered models to approaches focused on student competencies, a paradigm known as Competency-Based Learning (CBL) [World Economic Forum 2023]. Unlike passive memorization, CBL prioritizes the learner's ability to apply knowledge in practical contexts by articulating the triad of knowledge, skills, and attitudes. In this scenario, assessment becomes a continuous and complex process, requiring educators to understand not only "what" the student knows but "what" they are capable of performing with that knowledge [Idrissi et al. 2016].

Despite the proliferation of Learning Management Systems (LMS), the automated analysis of student progress faces significant semantic challenges. Most data generated

by traditional Learning Analytics (LA) tools lack a formal structure that allows for interoperability and automated inference regarding proficiency levels. A "semantic gap" exists between raw interaction data and the formal representation of competencies, which hinders the personalization of learning paths at scale.

While established standards exist in the literature, they often fail to capture the granularity of relationships between learning resources, assessment instruments, and the various proficiency levels required by both academia and the labor market. To address this gap, this paper presents *OntoLearn*, an ontology developed under the rigor of Description Logic (DL) to provide a foundation for competency analysis in virtual environments. *OntoLearn* was designed to serve as the semantic core of LA systems, enabling the relationship between student performance and competency acquisition to be processed in a computationally verifiable manner.

This work details the technical modeling of the ontology, its compliance with Semantic Web standards (OWL/XML), and its validation through a hybrid approach that integrates logical reasoners and generative artificial intelligence. The remainder of this paper is organized as follows: Section 2 presents the theoretical background on CBL and the Semantic Web; Section 3 discusses related work; Section 4 describes the methodology and architecture of *OntoLearn*; Section 5 details the validation results; and finally, Section 6 presents the conclusions and future perspectives.

2. Theoretical Background

This section establishes the conceptual foundations that support *OntoLearn*, focusing on Competency-Based Learning and the role of the Semantic Web in formal knowledge representation.

2.1. Competency-Based Learning (CBL)

The Competency-Based Learning (CBL) paradigm redefines the educational process by shifting the focus from content delivery to the practical application of knowledge. Within this framework, competency is defined as the ability of an individual to mobilize cognitive resources to effectively address complex situations [Idrissi et al. 2016]. The literature converges on a multidimensional structure composed of three fundamental axes [Sampson and Fytros 2008]:

- **Personal Characteristics:** The KSA triad (*Knowledge, Skills, and Attitudes*), which defines what the learner knows, what they are capable of doing, and how they behave.
- **Proficiency Level:** A classification that categorizes the learner's mastery over a specific competency (e.g., beginner, intermediate, advanced).
- **Context:** The environment or technical domain where the competency is applied and assessed.

2.2. Semantic Web and Ontologies

For CBL to be machine-processable, a formal and explicit representation of knowledge is required. The Semantic Web provides the framework for this formalization, using ontologies as the structural backbone. An ontology is defined as a formal specification of a shared conceptualization [Gruber 1993].

In the development of OntoLearn, Description Logic (DL) serves as the logical foundation to ensure model consistency. The adoption of the *Web Ontology Language* (OWL) standard allows for the definition of classes, object properties, and axioms. Unlike traditional relational models, OWL ontologies enable the use of reasoners to infer new knowledge—a critical functionality for automatically evaluating whether a student has achieved a certain competency level based on interaction data [Noy et al. 2001].

3. Related Work

To establish the formal domain requirements and identify conceptual gaps for OntoLearn, a Systematic Literature Review (SLR) was conducted following the PRISMA 2020 guidelines [Page et al. 2021] and the PICOC protocol. Five databases (ACM, IEEE, ScienceDirect, Scopus, Wiley) were searched for the period 2008–2022, using the base string (“*competency-based*” OR “*competence*”) AND (“*assessment*” OR “*evaluation*”) AND (“*virtual learning environment*” OR “*LMS*” OR “*e-learning*”), adapted to each engine’s syntax. Inclusion criteria required peer-reviewed primary studies addressing the assessment or analysis of specific competencies in virtual learning environments; we excluded secondary studies, non-English/Portuguese papers, and works without empirical or technical evaluation. The workflow retrieved 2,447 records, reduced to 28 primary studies after screening and a formal Quality Assessment (QA) phase. The full protocol (search strings per database, criteria, and QA rubric) is available in the project repository (see the *Artifact Availability* section).

The synthesis revealed a critical gap between evaluation formats (RQ1) and analytical techniques (RQ2). Traditional instruments like quizzes/MCQs predominate (58.3%, $N = 14$), offering scalability but lacking a semantic layer to link responses to structured competencies [Idrissi et al. 2016]. Conversely, personalization engines (28.6% Adaptive Learning; 21.4% competency models) often operate as “black boxes” [Susnjak et al. 2022] or rely on static context structures that lack automated reasoning properties (e.g., transitivity), preventing the automated inference of prerequisite paths across ecosystems.

Table 1 positions OntoLearn against these benchmarks, using three technical dimensions selected for their necessity in competency-based frameworks: *KSA Support* (pedagogical validity) [IEEE 2007], *Formal Reasoning* (prerequisite for dynamic discovery), and *LMS Integration* (readiness to ingest raw interaction logs) [Susnjak et al. 2022]. Each cell was classified by the authors through content analysis of the original publications and specifications, using fixed criteria per dimension: *KSA Support* reflects which triad elements are explicitly modeled; *Formal Reasoning* reflects the documented inference mechanism (none, taxonomic, or DL-based); and *LMS Integration* reflects the level of interoperability with interaction data reported by each work.

4. The OntoLearn Ontology

This section details the formal engineering of OntoLearn, a model designed to provide a semantic bridge between raw LMS interaction data and pedagogical competency frameworks.

Table 1. Comparative analysis of OntoLearn against related standards and models.

Work / Model	KSA Support	Formal Reasoning	LMS Integration	Validation Type
IMS RDCEO / IEEE RCD	Partial (Knowledge)	No	Static / Manual	Interoperability
Sampson and Fytros (2008)	Knowledge / Skills	Limited	Partial	Theoretical
Idrissi et al. (2016)	Full KSA Triad	Basic (Taxonomic)	Low	Expert Review
Raad and Cruz (2015)	N/A (Survey)	Varies by model	Identified Gap	Evaluation Survey
OntoLearn (Ours)	Full (KSA/CHA)	OWL DL / Transitive	Conceptual (xAPI-ready)	Hybrid (Reasoner+AI)

4.1. Ontology Engineering Approach

The development of OntoLearn followed a hybrid agile approach. We utilized the foundational structural steps of the Ontology Development 101 methodology [Noy et al. 2001] for domain initialization and hierarchy definition. However, to meet the requirements of modern Learning Analytics, the formalization and validation phases were conducted through iterative refinement cycles inspired by the SAMOD (*Simplified Agile Methodology for Ontology Development*) framework [Peroni 2017], including structural verification with OOPS! and axiomatization.

Figure 1 illustrates the integration of these methodologies into a unified workflow, while Table 2 maps the core engineering stages to the technical activities performed during the research.

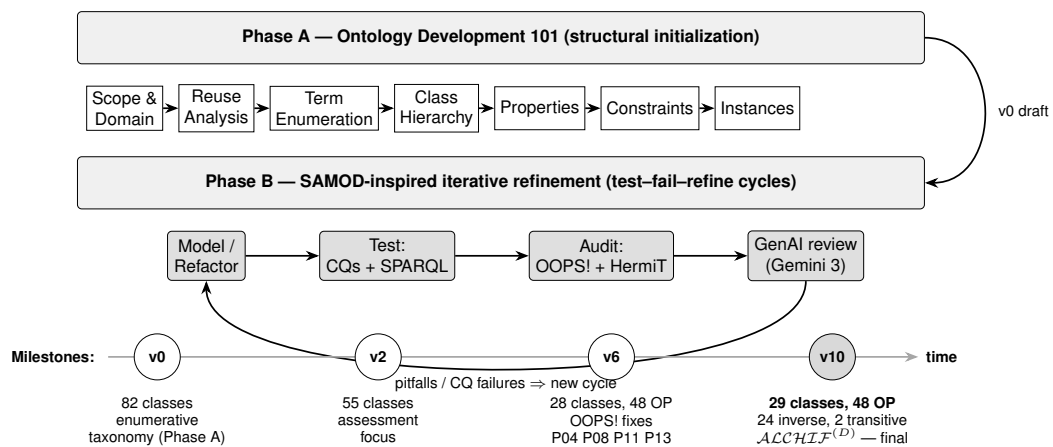


Figure 1. OntoLearn engineering workflow: Method 101 initialization (Phase A) followed by SAMOD-inspired refinement cycles (Phase B), with the resulting version milestones.

Table 2. OntoLearn Engineering Stages and Technical Activities.

Phase	Technical Activity
Scope	Focused on KSA triad and Learning Analytics requirements.
Hierarchy	Defined core classes: C01-Competency, C05-Proficiency, C08-Assessment, and C10-Resource.
Refinement	Applied SAMOD-inspired iterative cycles for prompt-based validation with Gemini 3.
Axiomatization	Implemented OWL 2 DL axioms (disjointness, inverse and transitive properties) to enforce pedagogical constraints.

4.2. Competency Questions (CQs) Definition

To ensure the ontological design directly addresses the core challenges of competency-based assessment and learning analytics, we defined a systematic set of Competency Questions (CQs) derived from our SLR findings. These CQs act as formal functional requirements that guided the iterative refinement cycles of the OntoLearn model and its functional validation. The questions are defined as follows: (CQ1) Which specific competencies has a given learner demonstrated? (CQ2) What is the proficiency level (Bloom’s Taxonomy) achieved by a learner in a specific competency? (CQ3) Which assessments in the VLE are mapped to evaluate competency ”X”? (CQ4) What are the direct and indirect prerequisites required to start competency ”Y”? (CQ5) Which learning resources address competency ”Z”? (CQ6) Which learners have reached the ”Apply” proficiency level in ”Programming”? (CQ7) What are the URLs of resources accessed by a learner in their development history for a specific competency? (CQ8) Is there a disparity between the learner’s proficiency in objective versus subjective assessment tasks?

4.3. OntoLearn Architecture and Semantic Schema

The architecture of OntoLearn is structured to support high-granularity analysis of student progress. The core schema, depicted in Figure 2, illustrates the interconnections between the KSA dimensions and the educational artifacts.

The model distinguishes between theoretical Knowledge, practical Skills, and Attitudes as disjoint components of a Competency. This separation allows the system to identify whether a student’s difficulty is conceptual or application-based. The relational logic is governed by object properties such as *competenciasAvaliadas* (linking questions to competencies) and *proficienciaAtingida* (linking performance records to Bloom-based proficiency levels).

4.4. Formalization and Logical Constraints

The formal layer of OntoLearn is grounded in Description Logic (DL). The final model is classified by Protégé as $\mathcal{ALCHIF}^{(D)}$, a fragment of the OWL 2 DL profile that balances expressive power (class hierarchies, inverse and functional properties, datatypes) with computational tractability. Combined with the declaration of transitive properties (`owl:TransitiveProperty`), this expressivity supports the automated inferences that simpler taxonomic models cannot execute.

Transitivity is essential for automated learning path discovery. The property *is-*

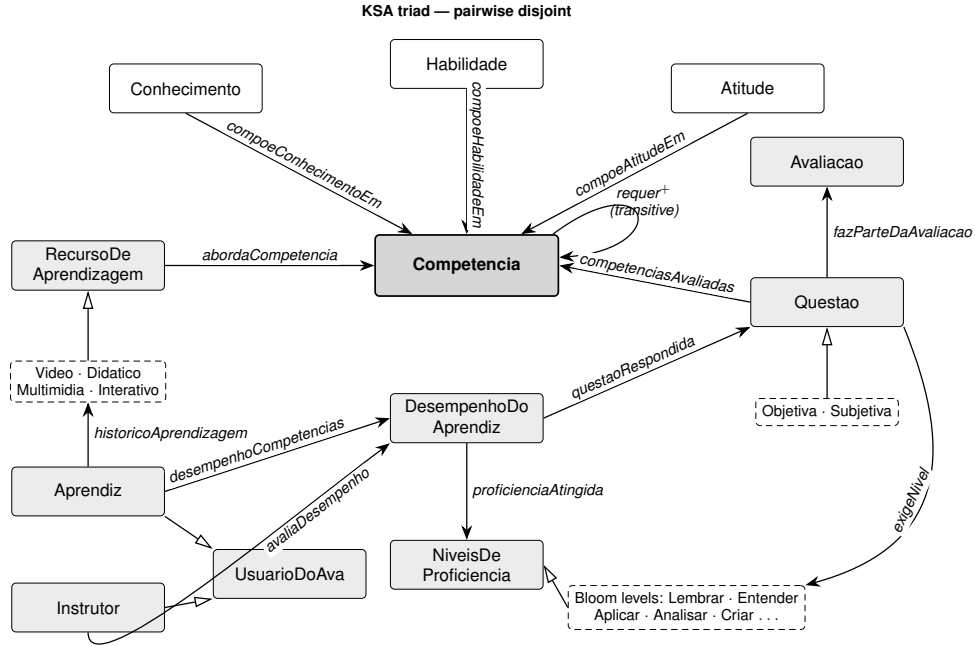


Figure 2. OntoLearn semantic schema: core classes and object properties extracted from the final model (v10). Open-triangle arrows denote subsumption; the transitive `requer` loop underpins prerequisite chain inference. Full documentation in the project repository.

*PrerequisiteOf*¹ is defined as transitive ($isPrerequisiteOf^+ \sqsubseteq isPrerequisiteOf$), allowing the reasoner to calculate full dependency chains. If "Basic Logic" is a prerequisite for "Algorithm Design", and the latter is a prerequisite for "Data Structures", the system automatically infers that a student must master "Basic Logic" before attempting "Data Structures".

To maintain the semantic integrity of the KSA triad, we implemented disjointness axioms. This ensures that the system prevents logical inconsistencies during the automated classification of student evidence, as a single learning objective cannot simultaneously be a theoretical concept and a behavioral trait:

$$Knowledge \sqcap Skill \sqsubseteq \perp, \quad Knowledge \sqcap Attitude \sqsubseteq \perp, \quad Skill \sqcap Attitude \sqsubseteq \perp \quad (1)$$

Furthermore, existential restrictions ($\exists$) are applied to guarantee that educational artifacts are always linked to their pedagogical purposes. We formalized that every *Assessment* (C08) must evaluate at least one *Competency* (C01) to be considered valid evidence within the Learning Analytics engine:

$$Assessment \sqsubseteq \exists evaluatesCompetency.Competency \quad (2)$$

¹Property and class names are presented in English for readability; the actual ontology IRIs are in Portuguese. *isPrerequisiteOf* corresponds to `:ehRequeridaPor`, declared as `owl:inverseOf:requer` (*requires*); both are transitive. Similarly, *evaluatesCompetency* corresponds to `:competenciasAvaliadas`. The C0x codes used in this paper are editorial shorthand, not ontology IRIs.

The model also utilizes qualified cardinality ($\mathcal{Q}$) and data property restrictions ($\mathcal{D}$) to define proficiency thresholds. For example, a student is only classified into a specific *ProficiencyLevel* ($C05$) if their *hasScoreValue* data property meets the minimum requirement defined for that competency. This formalization ensures that the "Gap Analysis" performed by the system is based on objective, verifiable logical rules rather than hard-coded heuristics, allowing OntoLearn to scale across different educational domains while maintaining rigorous pedagogical standards.

4.5. Implementation Metrics

OntoLearn was implemented in Protégé 5.5 and consolidated through successive refinement cycles. Table 3 traces the structural evolution of the model, whose final version was verified as 100% satisfiable by the HermiT reasoner. The earliest version enumerated entire knowledge domains and educational levels as classes (82 classes, e.g., *Agriculture*, *Law*, ISCED-based education levels); successive OOPS! audit cycles — which flagged pitfalls P04, P08, P11, P13, P20, and P41 — replaced this enumerative taxonomy with a leaner, domain-agnostic relational core: fewer classes (29), but substantially richer relational semantics (48 object properties, 24 declared inverses, 2 transitive properties). This consolidation pattern (hierarchy giving way to connectivity) is a known indicator of maturity in ontology engineering and directly answers how the Method 101 baseline was refined through SAMOD-inspired iterations.

Table 3. Evolution of OntoLearn across OOPS!/SAMOD refinement cycles (metrics from Protégé).

Metric	v0	v2	v6 (post-OOPS!)	v10 (final)
Classes	82	55	28	29
Object Properties	—	26	48	48
Data Properties	—	0	27	27
Inverse Properties	—	4	24	24
Transitive Properties	—	1	2	2
Individuals (test ABox)	0	0	32	40

Beyond structural metrics, the practical value of the model lies in what the reasoner derives automatically. Two mechanisms mitigate the instructor's cognitive load: **Automated Prerequisite Discovery** — through transitive properties, the reasoner materializes full dependency chains, identifying not just the immediate missing knowledge but root conceptual gaps (e.g., inferring that a student's struggle with 'Inheritance' stems from a lack of mastery in 'Class Definition'); and **Dynamic Competency Mapping** — when an assessment or resource is updated, proficiency status is recalculated across the dependency graph without manual intervention. The correctness of these inferences was verified manually against the gold standard during the CQ validation cycle (Section 5).

5. Validation and Results

The validation of OntoLearn followed a hybrid framework designed to ensure logical consistency and functional utility. This approach combines automated reasoning for technical verification with Generative Artificial Intelligence (GenAI) for semantic "stress-testing" and query generation, following the *human-in-the-loop* paradigm [Raad and Cruz 2015].

5.1. Layer 1: Technical and Structural Verification

The first stage focused on the intrinsic quality of the model, employing a dual-layer technical verification. First, we used the HermiT 1.4.3 reasoner to perform a full consistency check, ensuring that the complex axioms defined in Section 4.4 did not lead to logical contradictions. Second, we conducted a structural audit using OOPS! (Ontology Pitfall Scanner) to identify and mitigate common modeling pitfalls, such as redundant hierarchies or missing labels, ensuring the architectural robustness of the schema.

The results confirmed that OntoLearn is 100% consistent. Beyond consistency, the reasoner materialized the expected inferred knowledge — transitive prerequisite chains via `:requer`, inverse property assertions, and inferred class memberships — all of which were manually verified against the gold standard during the CQ validation cycle (Section 5.2).

5.2. Layer 2: Functional Validation and SPARQL Unit Testing

The second layer evaluated if the ontology could effectively answer the Competency Questions (CQs) required for Learning Analytics, following the structural evaluation criteria established by [Monfardini et al. 2023]. We implemented a SPARQL Unit Testing Suite where Google Gemini 3 acted as a semantic assistant to translate natural language CQs into formal queries, using the structured prompt template shown in Listing 1. All interactions used Gemini 3 in its extended-reasoning configuration (Gemini 3 Pro), accessed via the web interface in November 2025, with default generation parameters. For each CQ, a gold-standard answer set was defined manually by the authors prior to query generation, derived directly from the asserted and expected inferred facts of the synthetic ABox. A generated query was counted as correct only when it was syntactically valid and its result set matched the gold standard exactly (no missing or spurious bindings); partial matches were counted as errors. All generated queries were executed against the ABox in Protégé (SPARQL plugin), and their outputs were reviewed independently by two of the authors against the gold standard; disagreements were resolved by consensus.

The observed errors fell into two categories: (i) hallucinated vocabulary, where the model used property or class names absent from the schema (e.g., inventing *hasPrerequisite* instead of *requer*); and (ii) incomplete inference handling, where the query omitted the transitive operator (+), returning only direct prerequisites. All failing queries were corrected manually before integration into the test suite.

```
You are an expert in Semantic Web and an experienced SPARQL programmer.

## OntoLearn Ontology Context:
The ontology describes the domain of competency-based Learning
Analytics. Main classes: 'Aprendiz' (Learner), 'Competencia',
'DesempenhoDoAprendiz', 'RecursoDeAprendizagem', 'Avaliacao',
and 'Questao' (subclasses 'Objetiva', 'Subjetiva').
Main properties:
- :desempenhoCompetencias (Aprendiz -> DesempenhoDoAprendiz)
- :proficienciaAtingida (DesempenhoDoAprendiz -> NiveisDeProficiencia)
- :questaoRespondida (DesempenhoDoAprendiz -> Questao)
- :competenciasAvaliadas (Questao -> Competencia)
- :requer (Competencia -> Competencia, Transitive)
- :abordaCompetencia (RecursoDeAprendizagem -> Competencia)
Base prefix: <http://www.ontolearn.com/ontologia#>

## Task:
Translate the following Competency Question (CQ), given in natural
```

```
language, into an executable SPARQL query. Use STR() to compare
labels if necessary. Return only the SPARQL code block.
```

```
## Competency Question (CQ): [CQ from Section 4.2]
```

Listing 1. Prompt template used to instruct Gemini 3 for SPARQL generation (translated from Portuguese).

The validation followed an iterative test–fail–refine cycle. In the initial cycle, four CQs failed: CQ4 returned only direct prerequisites (the *requer* property lacked transitivity), CQ8 returned empty results (insufficient granularity to distinguish objective from subjective questions), CQ2/CQ3 exposed metadata inconsistencies, and CQ7 revealed an underpopulated ABox. After the corresponding corrective actions (e.g., redefining *requer* as `owl:TransitiveProperty`), all eight CQs were answered successfully in the final cycle (100% functional coverage). Additionally, the structural axioms were submitted to Gemini 3 for semantic plausibility assessment on a 1–5 Likert scale, yielding a mean score of 4.8/5. Listing 2 shows the final query for CQ4, retrieving direct and indirect prerequisites via the transitive operator.

```
1 PREFIX : <http://www.ontolearn.com/ontologia#>
2 PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
3
4 SELECT ?preReqLabel WHERE {
5   ?comp rdfs:label "Inheritance in Python" .
6   # The '+' operator performs a complete transitive search (direct and indirect).
7   ?comp :requer+ ?preReq .
8   ?preReq rdfs:label ?preReqLabel .
9 }
```

Listing 2. SPARQL query for transitive prerequisite verification (CQ4).

5.3. Case Study: Functional Simulation in a Programming Domain

To demonstrate the practical utility of OntoLearn, a functional case study was conducted using a purely synthetic dataset designed to simulate a Python Programming course environment. The test ABox comprises approximately 40 named individuals covering all core classes — simulated learners, competencies with prerequisite chains, performance records, objective and subjective questions, assessments, and learning resources — deliberately kept compact to allow full manual verification of every inference against the gold standard.

Crucially, this dataset was constructed “from scratch” based strictly on the logical constraints and axioms defined in the OntoLearn schema, without utilizing, deriving from, or being calibrated by real-world student logs or any institutional databases. Since the study does not involve real human subjects, personal data, or traces of actual academic behavior, it falls outside the scope of the Brazilian General Data Protection Law (LGPD) and, under current regulations, does not require Institutional Research Board (CEP/CONEP) approval, being characterized as a technical validation of a computational model. This exemption applies strictly to the present experiment: any future deployment of OntoLearn with real student data will require ethical review, informed consent, and full LGPD compliance measures. It is important to emphasize that this study focuses exclusively on verifying the ontology’s ability to maintain logical integrity and perform automated inferences in a closed system, and does not aim to measure pedagogical effectiveness in real-world educational contexts.

5.3.1. Semantic Graph of Validation

Figure 3 presents a focused subgraph of the validation scenario for learner APR-0001. Solid edges are facts asserted in the ABox; dashed edges are assertions materialized by HermiT. From seven asserted facts, the reasoner derived the inverse relations (e.g., *ehRequeridaPor*, linking COMP-0001 back to COMP-0002) and the subsumption-based class memberships (e.g., DEMP-0003, asserted as *Formativo*, inferred as *DesempenhoDoAprendiz*). This illustrates how OntoLearn propagates knowledge through the logical chain connecting learners, performance records, questions, proficiency levels, and competencies.

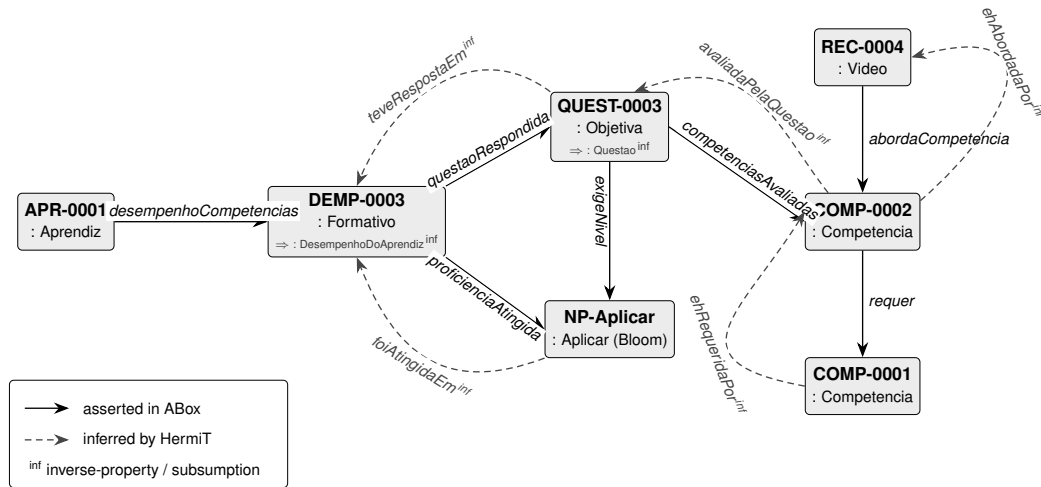


Figure 3. Validation scenario for learner APR-0001: asserted facts (solid) vs. assertions inferred by HermiT (dashed), extracted from the final ABox.

5.4. Analysis and Pedagogical Implications

The results demonstrate that OntoLearn effectively provides a semantic bridge between raw interaction data and high-level competency analysis. The use of GenAI as a validator proved to be a powerful method for Semantic Stress Testing, identifying potential ambiguities in class naming and property constraints that traditional reasoners would ignore. This hybrid approach ensures that the ontology is logically sound and aligned with structural requirements.

One critical finding was the effectiveness of the transitive prerequisite chain. In the tested cases, the system correctly identified students attempting to access "Advanced" content while missing "Basic" prerequisites in the semantic graph. This offers a technical framework that, if integrated into real systems, has the potential to assist instructors in identifying specific learning difficulties and preventing cognitive overload.

Beyond technical metrics, OntoLearn provides indications that semantic formalization can support Data-Driven Decision Making. By utilizing the OntoLearn proficiency graph, a teacher may eventually distinguish whether a student's difficulty is a theoretical gap (C02-Knowledge) or a practical application gap (C03-Skill). Such precision, when implemented in production environments, has the potential to optimize in-

structional time and support personalized interventions, such as assigning specific C10-LearningResources only to the subset of students that the ontology has flagged as lacking that specific skill.

A specific ethical consideration concerns the Attitude dimension (C04). Unlike Knowledge and Skills, which can be evidenced by assessment outcomes, attitudes (e.g., engagement, persistence) are latent constructs whose inference from interaction logs is inherently uncertain and susceptible to bias — a student’s low activity may reflect external constraints rather than disengagement. In the current model, Attitude instances are treated as declared evidence rather than automatically inferred states, and no axiom derives attitudinal judgments from behavioral traces. We argue that any future automated inference of attitudes must be validated with human oversight, communicated to students transparently, and never used as a sole basis for pedagogical or evaluative decisions.

5.5. LMS Integration and Data Ingestion

While the current validation focused on the logical integrity of the OntoLearn model in a controlled environment, its architecture was explicitly designed to support the ingestion of real-world educational trace data. To bridge the gap between abstract competency modeling and pragmatic Learning Analytics, OntoLearn adopts a design compatible with interoperability standards, specifically xAPI (Experience API) and Caliper Analytics. The conceptual flow maps raw interactions (captured as xAPI statements: ‘actor’, ‘verb’, ‘object’) directly to core OntoLearn classes: Learner, Performance, and Resource. This design allows the ontology to function as a scalable semantic middleware, transforming heterogeneous activity streams into structured, competency-based insights without requiring architectural changes to existing LMS infrastructures.

6. Conclusions and Future Work

This paper presented OntoLearn, a formal ontology designed to enhance the analysis of Competency-Based Learning in digital environments. The main contributions include: (i) the formalization of proficiency levels and prerequisites through transitive, inverse, and functional axioms within the OWL 2 DL profile; (ii) a modular architecture that separates pedagogical objectives from educational resources; and (iii) a hybrid validation framework that combines automated reasoning (HermiT, OOPS!) with Generative AI (Gemini 3) under a human-in-the-loop paradigm.

The technical validation confirmed that the model is 100% logically consistent and, after an iterative refinement cycle, answered all eight Competency Questions successfully. It is critical to note, however, that this study serves as a proof-of-concept of the model’s formal reasoning capabilities in a controlled, synthetic environment, and not as an empirical validation of pedagogical efficacy in actual classrooms.

Some limitations were identified. The model was tested only within the computer science domain (Python programming) and on a compact synthetic ABox (~40 individuals); its performance with real-world data and large-scale datasets remains unverified. Furthermore, the model is relatively static, requiring manual intervention for major pedagogical updates.

Future work will focus on: validation in real educational settings with LMS data, including evaluation by instructors and domain experts; cross-domain expansion to sub-

jective areas, with particular attention to fair and transparent modeling of the Attitude dimension; the implementation of fuzzy logic for proficiency thresholds; and the integration of the semantic core into real-time teacher dashboards.

Artifact Availability

To support reproducibility, all research artifacts are publicly available at <https://doi.org/10.5281/zenodo.21441488>: the OntoLearn OWL file, the eight CQs and their final SPARQL queries, the synthetic ABox dataset, the Gemini 3 prompt template, and the full SLR protocol (search strings per database, inclusion/exclusion criteria, and quality assessment rubric).

Declaração sobre uso de Inteligência Artificial (AI Usage Statement)

In compliance with the SBC Code of Conduct and CNPq Ordinance No. 2664/2026, the authors declare that Google Gemini 3 (extended-reasoning mode, accessed November 2025) was used as a methodological assistant during the functional validation phase (Section 5), specifically for translating CQs into SPARQL queries (prompt in Listing 1) and for the semantic plausibility assessment of axioms. All outputs were executed, verified, and, when necessary, corrected by the authors under a human-in-the-loop paradigm. The authors remain fully responsible for the intellectual content and all ontology design decisions.

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