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# Evaluation of an Intelligent Electronic Prescription Ontology Using Open Source Tools: A Botswana Case Study

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**Abstract:** Healthcare interoperability in Botswana is hindered by fragmented information exchange across public and private providers, resulting in prescription conflicts, duplicated treatment, and delayed care. In prior work, we developed the Intelligent Electronic Prescription Ontology (IEPO), an open-source OWL 2 ontology for semantically standardized prescription data exchange. Although IEPO was previously validated using competency question-driven metrics (recall, precision, and F1-score), those measures did not assess ontology structural quality or schema-level expressiveness. This paper presents a post-development evaluation of IEPO using two opensource ontology assessment tools: The Ontology Pitfall Scanner (OOPS) and OntoMetrics, with the Prescription of Drug Ontology (PDRO) used as a benchmark. OOPS identified initial IEPO modelling issues in consistency (60%) and completeness (40%), which were resolved through iterative refinement in Protégé, resulting in 0% residual detection error under the evaluated OOPS criteria. In contrast, PDRO retained 100% detection error across the reported OOPS categories in the baseline comparison. OntoMetrics further showed that IEPO outperformed PDRO in class richness (1.000 vs. 0.001), attribute richness (4.429 vs. 0.012), relationship richness (0.839 vs. 0.175), and axiom/class ratio (63.93 vs. 10.62), indicating stronger structural expressiveness and richer schema representation. These findings show that IEPO is not only functionally queryable but also structurally robust and semantically well formed according to open-source rule-based and quantitative evaluation criteria, strengthening its readiness for future standards-aligned e-prescription interoperability in Botswana's healthcare ecosystem.

**Keywords:** Healthcare Interoperability, Electronic Prescription, Ontology Evaluation, OOPS, OntoMetrics, Botswana Healthcare System

## Introduction

Healthcare interoperability refers to the ability of heterogeneous health information systems (including clinics, pharmacies, laboratories, and insurers) to exchange and interpret clinical data accurately and efficiently (Sathvika and Jeyalakshmi, 2026). In many developing settings, including Botswana, healthcare delivery remains fragmented across public and private providers, limiting continuity of care and weakening coordinated treatment workflows (Servan-Mori et al., 2026). This fragmentation contributes to duplicated procedures, delayed treatment decisions, inconsistent prescribing practices, and avoidable medication-related risks (Djochie et al., 2026).

Semantic web technologies and ontology-based modelling provide a practical approach to addressing such interoperability gaps by defining formal, machine-readable representations of healthcare concepts and relationships. Ontologies support shared vocabularies, semantic alignment, and consistent interpretation of prescription data across otherwise isolated healthcare systems (Mauer et al., 2026). While established standards and domain resources such as HL7 FHIR and other healthcare knowledge models provide strong interoperability foundations, adaptation to local clinical workflows can remain difficult due to implementation complexity, context mismatch, and integration overheads (Ojha et al., 2026).

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To address this challenge in the Botswana context, our previous work introduced the Intelligent Electronic Prescription Ontology (IEPO), an open-source OWL 2 ontology designed to support semantically enriched electronic prescription exchange among clinics, doctors, and pharmacies (Okon et al., 2024). Prior to IEPO development, we did an extensive literature review on ontology tools and approaches to building prescription frameworks with ontologies and the article is published here (Okon et al., 2025). IEPO was published online at https://github.com/tsigwele/IEPO and functionally validated using SPARQL-based competency questions with retrieval-oriented measures such as recall, precision, and F1-score (Okon et al., 2024). Although these results demonstrated functional queryability, they did not evaluate ontology engineering quality dimensions such as structural soundness, modeling correctness, schema expressiveness, and pitfall susceptibility.

This gap is particularly important in healthcare, where poorly structured ontologies may introduce ambiguous reasoning paths, semantic inconsistencies, and integration failures in safety-critical workflows (Ambalavanan et al., 2025). For deployment-oriented ontologies, it is therefore necessary to supplement competency question validation with explicit quality assessment using ontology engineering tools that can detect modeling pitfalls and quantify schema-level characteristics.

In this paper, we perform a systematic post-development evaluation of IEPO using two open-source ontology assessment tools: The Ontology Pitfall Scanner (OOPS) and OntoMetrics (Poveda-Villalon et al., 2014; Lozano-Tello and Gomez-Perez, 2004). OOPS provides rule-based pitfall detection for ontology quality diagnostics, while OntoMetrics provides quantitative measures of knowledge-base and schema richness. To contextualize the results, the Prescription of Drug Ontology (PDRO) is used as a benchmark ontology within the same domain (Ethier et al., 2021). The main contribution of this study is not the introduction of IEPO itself, but a comparative, tool-based structural and semantic quality evaluation of IEPO using openly accessible methods, including iterative refinement and reassessment. This contribution extends prior IEPO work by providing a reproducible ontology quality assurance workflow relevant to healthcare interoperability research, ontology maintenance, and standards-aligned e-health integration initiatives.

## *Ontology Evaluation Tools*

Table 1 summarizes selected ontology evaluation tools using usability-oriented characteristics relevant to this study, including graphical user interface availability, API support, installation requirements, editor independence, customization capability, and offline usage. The compared tools include OOPS (Poveda-Villalon et al., 2014), MoKi (Ghidini et al., 2009), OQuaRE (Duque-Ramos et al., 2011), XD Analyzer (Ondraszek et al., 2024), OntoCheck (Schober et al., 2012), Eyeball (Kolozali et al., 2014), and OntoMetrics (Lozano-Tello and Gomez- Perez, 2004).

Evaluating an ontology is a critical stage in ontology engineering, particularly when the ontology is intended for deployment in sensitive domains such as healthcare. Beyond logical correctness, ontology evaluation should assess structural quality, semantic richness, modelling clarity, and readiness for integration into heterogeneous systems. These ontology evaluation tools have been also categorized into web-based platforms, editor plug-ins, and desktop/API-driven solutions, each offering different levels of automation, accessibility, and metric coverage (Okon et al., 2025; Jaziri and Sassi, 2026).

Among the surveyed tools, OOPS and OntoMetrics provide a strong balance of accessibility, reproducibility, and complementary evaluation coverage for the objectives of this paper. OOPS is a web-based ontology pitfall scanner that requires no local installation and detects common modelling issues in OWL ontologies, including problems associated with consistency, completeness, and conciseness (Poveda-Villalon et al., 2014). It is particularly useful for iterative refinement because it reports diagnostically meaningful pitfalls and supports correction-oriented ontology engineering workflows.

OntoMetrics complements OOPS by providing quantitative measures of ontology knowledge base and schema properties, including class richness, attribute richness, relationship richness, axiom/class ratio, inheritance richness, and equivalence usage (Lozano-Tello and Gomez-Perez, 2004).

**Table 1:** Comparison of selected ontology evaluation tools based on usability-oriented characteristics used to justify tool selection in this study

| Feature Type | OOPS | MoKi | OQuaRE | XD Analyzer | Onto Check | Eye ball | Onto Metrics | Affected Tools (%) |
|---|---|---|---|---|---|---|---|---|
| GUI | ✓ | ✓ | ✓ | ✓ | ✓ | × | ✓ | 14% |
| API Support | ✓ | × | ✓ | × | × | ✓ | ✓ | 43% |
| No Installation | ✓ | × | ✓ | × | × | × | ✓ | 57% |
| Editor Agnostic | ✓ | × | ✓ | × | × | ✓ | ✓ | 43% |
| Customization | ✓ | × | × | × | × | ✓ | ✓ | 57% |
| Offline Use | × | ✓ | × | ✓ | ✓ | ✓ | × | 43% |
| Tool Gaps (%) | 14% | 57% | 29% | 57% | 57% | 29% | 29% | — |

These metrics enable comparative assessment of structural expressiveness, modelling balance, and representational depth across ontologies. In combination, OOPS and OntoMetrics support both diagnostic (pitfall-based) and quantitative (schema-level) evaluation, making them suitable for post-development quality assessment of an e-prescription ontology intended for healthcare interoperability.

Based on this rationale, the present study uses OOPS and OntoMetrics to evaluate the Intelligent Electronic Prescription Ontology (IEPO) and compares the results with the Prescription of Drug Ontology (PDRO) (Ethier et al., 2021) under the same tool conditions.

## Materials and Methods

### *IEPO Ontology Framework Overview*

Fig. 1 shows the semi-formal conceptual model of IEPO, which was developed in our prior work as an open-source semantic model for interoperable electronic prescription data exchange in Botswana (Okon et al., 2024). In the present paper, IEPO is treated as the ontology artifact under evaluation, and only the conceptual characteristics relevant to structural and semantic quality assessment are summarized. IEPO organizes prescription-domain knowledge around core entities such as Person, Prescription, Diagnosis, Appointment, and Drug. The model captures key healthcare actors (e.g., doctor, pharmacist, receptionist, and patient) together with prescription-related concepts used in prescribing and dispensing workflows. It also includes supporting concepts required for operational prescription management, such as dates, cost, dispense status, and interaction status, as well as appointment modalities.

This semi-formal conceptualization defines the domain scope, major class groupings, and high-level relationships that guide later ontology engineering activities. It provides the conceptual foundation that is subsequently transformed into a formal ontology during the Methontology formalization stage (next section) and serves as domain context for the evaluation reported in Section 3.

### *Ontology Formalization Overview*

Fig. 2 shows the IEPO formalization phase within the Methontology process, in which the semi-formal conceptual model in the previous section is transformed into a machine-processable ontology (Fernández-López et al., 1997). The output of this phase is the formal ontology file IEPO.owl, which is used for subsequent deployment and evaluation. The formalization workflow was implemented in Protégé (Musen, 2015) and focused on efficient ontology construction, axiom creation, and rule-based functionality development. A central step in this process was the preparation of IEPO object properties, data properties, and ontology individuals in spreadsheet form, followed by batch import into Protégé. Transformation rules and the Cellfie plugin were used to convert spreadsheet entries into ontology axioms and assertions, enabling rapid creation of linked ontology content in a single import workflow rather than manual entry of large numbers of assertions.

Within Protégé, these imported assertions were integrated with the IEPO class structure to establish links among classes, object properties, data properties, and individuals.

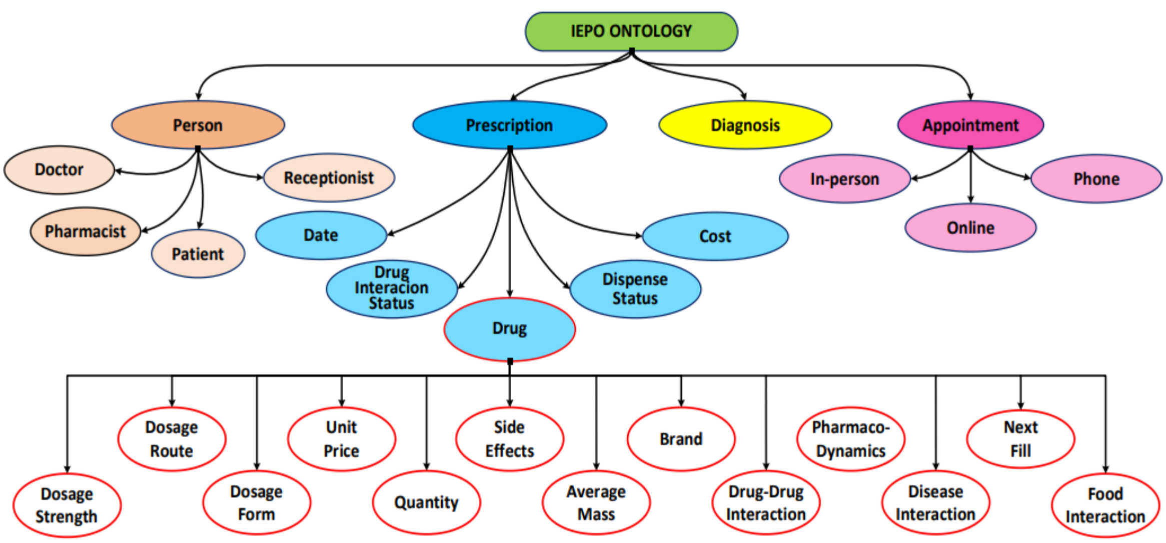


**Fig. 1:** Semi-formal conceptual model of IEPO (Okon et al., 2024)

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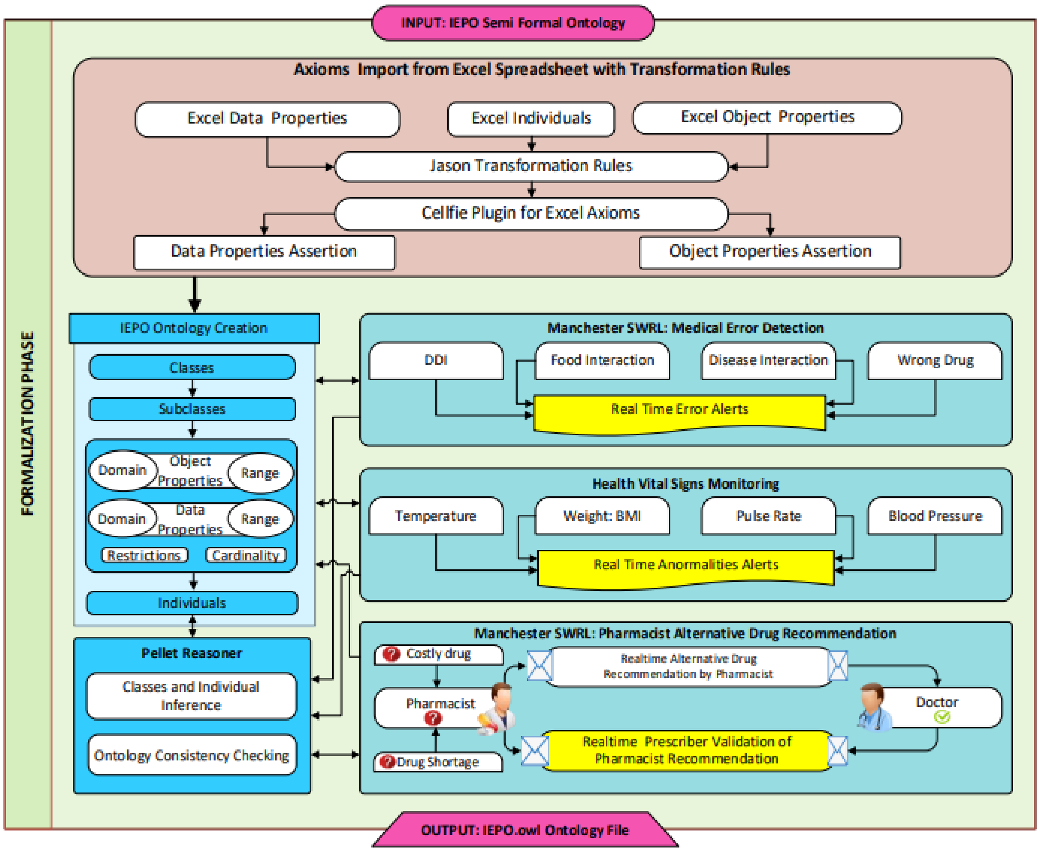


**Fig. 2:** IEPO formalization phase in Methontology

The Pellet reasoner was then used to support ontology consistency checking and inference generation, helping validate the formalized ontology structure and detect potential logical issues during construction.

The core IEPO functional capabilities were also implemented using Manchester SWRL rules. As summarized in Fig. 2, the major rule-based functionalities included medical error detection, health vital-sign monitoring, and pharmacist-oriented alternative drug recommendation/validation workflows. These rule layers extend the ontology beyond static representation by supporting domain-specific reasoning and alert generation.

The outcome of this stage is the formal IEPO ontology file (IEPO.owl), which constitutes the finalized ontology ready for the implementation, hosting, and querying stage described in the next subsection.

Implementation, Hosting, and Querying Context

Figure 3 shows the implementation, hosting, and querying workflow of the formalized IEPO ontology produced in the previous formalization stage. The input to this workflow is the IEPO.owl ontology file exported from Protégé, which is then used for publication, local hosting, and query-based access.

As summarized in Figure 3, the workflow comprises three main blocks:

(i) Ontology publishing on GitHub for open-source distribution and reproducibility
(ii) Ontology local hosting using an Apache Jena Fuseki server with a SPARQL endpoint
(iii) HTTP REST SPARQL querying for retrieving ontology knowledge

The Fuseki-hosted ontology provides an endpoint through which local Protégé queries and external HTTP requests can be executed against the IEPO knowledge base.

SPARQL query results are returned in interoperable formats such as JSON, XML, CSV, Turtle, and RDF triples, enabling integration and information sharing across different users and systems. As indicated in Figure 3, these query outputs can be consumed by healthcare and research stakeholders, including doctors, pharmacists, patients, researchers, and machine-based systems. In this study, the hosted IEPO ontology shown in this workflow served as the operational artifact used for subsequent OOPS and OntoMetrics evaluation.

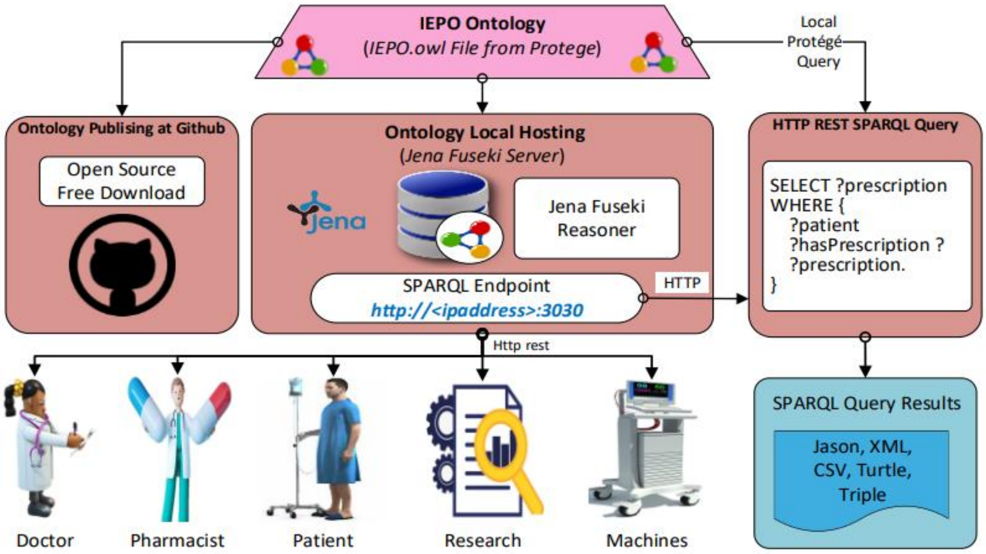


**Fig. 3:** IEPO implementation, hosting, and querying workflow

## Results and Discussion

IEPO and PDRO were evaluated under the same conditions using OOPS and OntoMetrics to compare ontology engineering quality beyond prior competency-question-based functional validation (Poveda-Villalon et al., 2014; Lozano-Tello and Gomez- Perez, 2004; Ethier et al., 2021). OOPS was applied to IEPO in two stages (initial scan and post-refinement re-scan after iterative correction in Protégé), while PDRO was used as a baseline under the same OOPS scanning criteria without a correction-and-rescan cycle. OOPS-based error rates were computed as proportions of detected pitfalls relative to the number of checked pitfalls using Eqs. 1–3. The initial detection error is given by:

$$E_{init}\,(\%)=\frac{\mathrm{N}_{\mathrm{detected}}}{\mathrm{N}_{\mathrm{detected}}}\times 100 \qquad (1)$$

Where $E_{init}$ (%) is the initial OOPS detection error percentage, $N_{\mathrm{detected}}$ is the number of detected pitfalls, and $N_{\mathrm{checked}}$ is the number of checked pitfalls in the evaluated category or dimension. The residual post-refinement error is:

$$E_{res}\,(\%)=\frac{\mathrm{N}_{\mathrm{remaining}}}{\mathrm{N}_{\mathrm{Checked}}}\times 100 \qquad (2)$$

Where $E_{res}$ (%) is the residual OOPS detection error percentage after refinement and $N_{\mathrm{remaining}}$ is the number of pitfalls still detected after correction. The refinement gain is:

$$G(\%)=E_{init}\,(\%)-E_{res}\,(\%) \qquad (3)$$

Where $G$ (%) denotes the percentage reduction in OOPS detection error after refinement.

OOPS pitfalls were evaluated at two levels. At the category level: Consistency (P05, P06, P07, P19, P24), completeness (P04, P10, P11, P12, P13), and conciseness (P02, P03, P21). At the dimension level: Structural (modelling decisions, wrong inference, no inference, ontology language), functional (real-world modelling, requirements completeness, application context), and user profiling (ontology clarity, ontology understanding, ontology metadata), each assessed using their corresponding OOPS pitfall sets.

OntoMetrics was subsequently applied to compute comparative knowledge base and schema level metrics (including class richness, attribute richness, relationship richness, and axiom/class ratio), with results reported in tabular form and visualized on a logarithmic scale to preserve interpretability across multiple metric magnitudes.

### *OOPS Results for Consistency, Completeness, and Conciseness*

Table 2 shows the category-level OOPS comparison of IEPO and PDRO across consistency, completeness, and conciseness. The results in the table shows that IEPO initially recorded 60% consistency error (3/5) and 40% completeness error (2/5), with 0% conciseness error. After refinement, IEPO achieved 0% residual error across all categories, whereas PDRO exhibited 100% detection error in consistency, completeness, and conciseness. IEPO's initial issues were limited to consistency (P05, P19, P24) and completeness (P10, P11), with no conciseness pitfalls detected.

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**Table 2:** IEPO and PDRO comparison: OOPS consistency, completeness, and conciseness

| OOPS Metric | IEPO Pitfalls Detected | IEPO Initial Error (%) | IEPO After Refinement (%) | PDRO Pitfalls Detected | PDRO Error (%) |
|---|---|---|---|---|---|
| Consistency | P05, P19, P24 | 60 | 0 | P05, P06, P07, P19, P24 | 100 |
| Completeness | P10, P11 | 40 | | P04, P10, P11, P12, P13 | |
| Conciseness | None | 0 | | P02, P03, P21 | |

The reduction from 60% and 40% to 0% demonstrates complete resolution of detected category-level issues under the evaluated OOPS rules. Overall, these results show that IEPO demonstrates substantially stronger OOPS-compliant modelling quality than PDRO under identical evaluation conditions.

### *OOPS Results for Dimension Based Evaluation*

Figure 4 shows the structural dimension comparison, which is the first component of the dimension-level OOPS analysis across structural, functional, and user-profiling categories. In the structural dimension, IEPO initially showed a 60% error for modelling decisions (detected: P05, P19, P24) and a 40% error for wrong inference (detected: P10, P11), while no errors were reported for no-inference and ontology-language categories. After iterative refinement, all structural-dimension errors were reduced to 0%. PDRO remained at 100% detection error across all reported structural categories under the baseline OOPS scan. These structural-dimension results indicate that IEPO achieved complete elimination of detected modelling and inference issues, demonstrating markedly stronger structural quality than PDRO under the same evaluation criteria.

Figure 5 shows that IEPO's functional pre-refinement errors were concentrated in real-world modelling (60%; P05, P19, P24) and application context (40%; P10, P11), with 0% in requirements completeness. After refinement, all functional errors were eliminated, while PDRO remained at 100%. The table also shows the user-profiling dimension, where IEPO initially had non-uniform errors: Ontology clarity (50%; P08), ontology understanding (22%; P08, P11), and ontology metadata (50%; P41). Post-refinement, IEPO achieved 0% residual error across all categories, whereas PDRO remained at 100%. Overall, these results demonstrate that IEPO consistently outperforms PDRO across functional and user-profiling dimensions, achieving targeted correction of all detected issues.

Figure 6 shows that IEPO's pre-refinement user-profiling errors were localized: Ontology understanding (22%) and ontology clarity and metadata (50%). Across all three dimensions, IEPO consistently reduced detected errors to 0% after refinement, while PDRO remained at 100% in all categories. These results confirm that IEPO achieves substantially stronger OOPS-compliant modelling quality than PDRO.

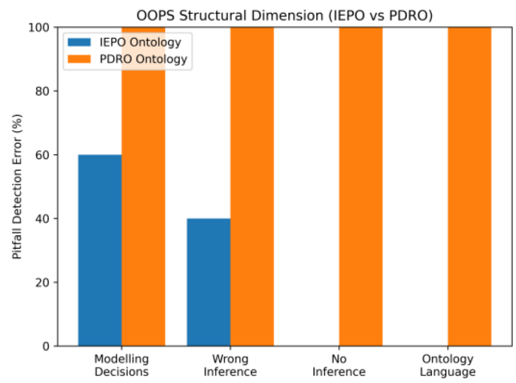


**Fig. 4:** Dimension-specific OOPS comparison for the structural dimension

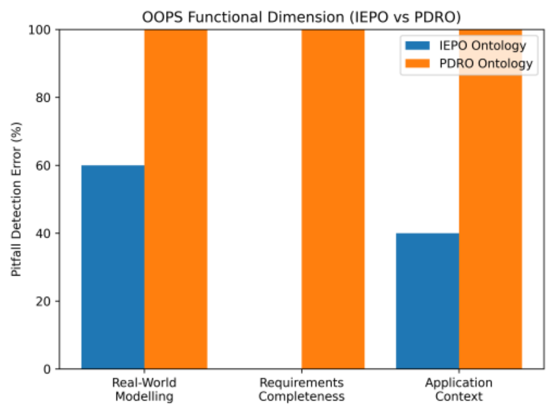


**Fig. 5:** Dimension-specific OOPS comparison for the functional dimension

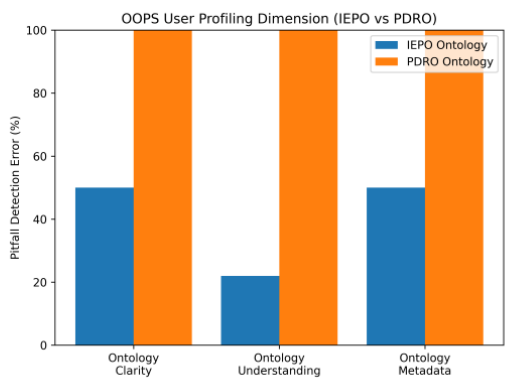


**Fig. 6:** Dimension-specific OOPS comparison for the user-profiling dimension

### *OntoMetrics Results*

Figure 7 presents the comparative OntoMetrics profile of IEPO and PDRO on a logarithmic scale, used to preserve visibility across metrics spanning $10^{-3}$ to $10^{2}$.

The logarithmic scale ensures clear comparison across high- and low-magnitude metrics. Table 3 reports the exact values.

IEPO clearly outperforms PDRO in representational coverage and schema expressiveness: Average population (2.786 vs. 0.001), class richness (1.000 vs. 0.001), attribute richness (4.429 vs. 0.012), relationship richness (0.839 vs. 0.175), and axiom/class ratio (63.93 vs. 10.62).

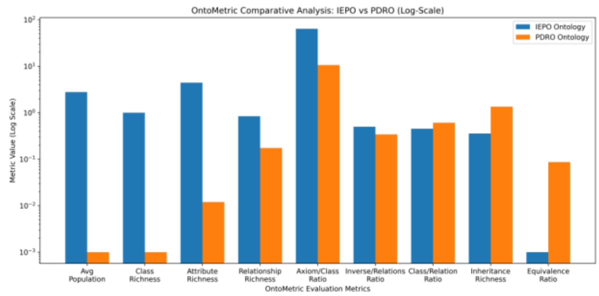


**Fig. 7:** Log-scale comparative visualization of OntoMetrics values for IEPO and PDRO

**Table 3:** OntoMetrics-based comparison of IEPO and PDRO across knowledge base and ontology-schema metrics

| Category | OntoMetrics Evaluation Metric | IEPO Ontology | PDRO Ontology |
|---|---|---|---|
| Knowledge Base | Average Population | 2.786 | 0.001 |
| | Class Richness | 1.000 | 0.001 |
| | Attribute Richness | 4.429 | 0.012 |
| | Relationship Richness | 0.839 | 0.175 |
| | Axiom/Class Ratio | 63.93 | 10.62 |
| Ontology Schema | Inverse/Relations Ratio | 0.500 | 0.342 |
| | Class/Relation Ratio | 0.452 | 0.610 |
| | Inheritance Richness | 0.357 | 1.352 |
| | Equivalence Ratio | 0.001 | 0.087 |

PDRO scores higher in class/relation ratio (0.610 vs. 0.452), inheritance richness (1.352 vs. 0.357), and equivalence ratio (0.087 vs. 0.001), reflecting deeper hierarchical emphasis. Overall, IEPO exhibits greater schema density and logical expressiveness, while PDRO emphasizes structural hierarchy.

## Conclusion

This study evaluated the Intelligent Electronic Prescription Ontology (IEPO) using OOPS and OntoMetrics, comparing it with the Prescription of Drug Ontology (PDRO). Unlike prior validations focused on functionality, this work assessed ontology quality, including modelling pitfalls, structure, and schema expressiveness. IEPO initially showed moderate consistency and completeness issues in OOPS but achieved 0% residual error after iterative refinement, while PDRO maintained 100% detection errors. IEPO's errors were localized and fixable, especially in modelling, inference, and user profiling. OntoMetrics results confirmed IEPO's superiority in key metrics like average population, class richness, attribute richness, and axiom/class ratio, reflecting richer representation and stronger schema expressiveness. Although PDRO excelled in inheritance richness and equivalence ratio, IEPO is overall better suited for e-prescription interoperability. Future work will focus on standards alignment, SHACL validation, and real-world e-health deployment evaluation.

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## Author's Contributions

All authors contributed to the conceptualization, methodology, analysis, and writing of the manuscript, and approved the final version.

## Ethics

This study did not involve human participants or animals, and no ethical approval was required.

### *Conflict of Interest*

The authors declare no conflict of interest.

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