Improving Reproducibility in Ontology-Based Data Generation: A Framework and Case Study

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***Abstract*—The exponential growth of heterogeneous data across domains such as healthcare, cybersecurity, and industry has intensified the need for robust semantic organization mechanisms. Ontology-based data generation (OBDG) offers a powerful approach to automatically structure knowledge and enrich information sources through techniques ranging from traditional entity extraction to modern LLM-based generation. However, despite significant methodological advances, a critical reproducibility gap persists, undermining the reliability and adoption of OBDG systems. This paper addresses this challenge through three main contributions: (1) a systematic analysis of reproducibility barriers in current OBDG research, examining issues with resource accessibility, documentation, and evaluation standardization; (2) a structured four-step assessment framework covering accessibility, executability, comparability, and generalizability, accompanied by a practical checklist for authors; and (3) empirical validation through case studies on conversational interfaces and robotics systems. Our analysis reveals that only a minority of OBDG systems provide complete replication packages, with most offering partial or no access to essential resources. The proposed framework successfully identifies key reproducibility bottlenecks and provides actionable guidelines for improving transparency, supporting the development of more robust OBDG systems for real-world applications.**

I. Introduction

The exponential growth of heterogeneous data across critical domains such as healthcare [1], cybersecurity [2], and industry [3] has intensified the need for robust semantic organization mechanisms. Ontologies provide a formal framework for structuring domain knowledge through concepts, relationships, and logical constraints, enabling machine-interpretable representation and automated reasoning [4], [5]. Unlike traditional databases, ontologies enhance interoperability, support heterogeneous data integration, and facilitate large-scale knowledge management [1], [3]. Consequently, ontology-based data generation (OBDG) has emerged as a critical approach to automatically populate and enrich ontologies from diverse sources, including relational databases [5], unstructured text [1], simulation models [3], and social networks [6].

Recent advances in OBDG techniques including LLM-based generation [7], [8], ontology-guided annotation [9], [10], SWRL reasoning [11], and D2T transformation [1], [12] have demonstrated significant potential for automating knowledge extraction and structuring. These approaches enable diverse applications ranging from biomedical annotation [1], [13] and cybersecurity knowledge graph generation [2], [11] to industrial workflow automation [3], [14] and educational content creation [15]. However, despite these methodological innovations, a critical challenge persists: the widespread lack of reproducibility and standardized evaluation in OBDG research. Numerous studies report promising results but fail to provide complete access to source code, datasets, or configuration details [11], [16], severely limiting experimental validation and cross-system comparison. This reproducibility gap undermines the reliability, scalability, and real-world adoption of OBDG systems, particularly in high-stakes domains where accuracy and transparency are paramount.

Current OBDG research faces significant hurdles in resource accessibility, evaluation standardization, and generalizability testing. To address these challenges, this paper proposes a structured framework for assessing and improving reproducibility in ontology-based data generation. Our approach systematically addresses the identified gaps through three key contributions:

- A comprehensive analysis of reproducibility barriers in current OBDG literature, examining issues with resource accessibility, documentation quality, and evaluation standardization across multiple application domains.
- A novel four-step assessment protocol covering accessibility evaluation, executability verification, performance comparability, and generalizability testing, accompanied by practical implementation guidelines.
- Empirical validation through detailed case studies of representative systems DataBot [16] (conversational interfaces) and OG-SGG [9] (robotics scene generation) demonstrating the framework's utility in identifying reproducibility bottlenecks and guiding improvements.

The proposed framework establishes concrete best practices and encourages open-science standards in OBDG research. By addressing the reproducibility gap, our work aims to enhance the reliability, transparency, and practical adoption of ontology-based data generation systems across diverse application domains.

The remainder of this paper is organized as follows: Section II reviews background concepts and related work, highlighting reproducibility gaps. Section III presents our reproducibility assessment framework. Section IV details case studies applying the framework. Section V discusses implications and limitations. Finally, Section VI concludes with future research directions.

II. Background and Related Work

A. Ontology Fundamentals and Key Techniques

Ontologies provide a formal framework for structuring domain knowledge through concepts, relationships, and logical constraints, enabling machine-interpretable representation and automated reasoning. The canonical structure of an ontology comprises four complementary components: the *TBox* defining the conceptual taxonomy, the *RBox* specifying semantic relations and properties, the *ABox* containing concrete instances, and *axioms* encoding logical constraints and inference rules [4], [17]. This structured representation enables semantic consistency and automated reasoning across heterogeneous systems.

The Semantic Web stack provides essential technologies for ontology implementation and data generation. RDF (Resource Description Framework) represents information as triples (subject, predicate, object), forming the foundation for knowledge graphs. OWL (Web Ontology Language) extends RDF with expressive modeling capabilities through classes, properties, and logical axioms, facilitating inference of implicit knowledge [18]. SPARQL serves as the query language for interrogating and manipulating RDF/OWL graphs, enabling instance extraction and complex query execution.

Key techniques for ontology-based data generation include:

- **Named Entity Recognition (NER)**: Identifies relevant concepts in unstructured texts for ontological annotation [19], [20].
- **Large Language Models (LLMs)**: Generate ontological definitions and derive structured knowledge from documents [7], [8].
- **Semantic Web Rule Language (SWRL)**: Formalizes domain rules for implicit knowledge deduction through symbolic reasoning [11].
- **Data-to-Text (D2T)**: Transforms structured ontological data into natural language descriptions for improved interpretability [1], [12].
- **Transformer Models**: Generate contextual embeddings capturing conceptual similarity and semantic relations [3].

B. Typology of Ontology-Based Data Generation Approaches

Research on automatic data generation within ontologies spans diverse application domains and can be categorized according to two primary paradigms:

1) Generation Through Ontologies

This paradigm exploits the formal structure of a domain model to guide the automatic creation, enrichment, or inference of instances, relations, and recommendations. Ontological concepts, properties, and axioms actively constrain and drive the generation process, ensuring semantic coherence and consistency. Approaches in this category leverage ontologies as generative engines for tasks such as personalized recommendation [21], workflow composition [11], and decision support. Other applications include action recognition in sports videos [10] and home care services [22].

2) Generation Towards Ontologies

This paradigm focuses on extracting, transforming, and structuring heterogeneous data to populate or enrich ontologies. Input sources include relational databases [5], unstructured texts [23], simulation models [3], and domain-specific corpora. Techniques range from schema mapping and conceptual alignment for relational data transformation to entity extraction and semantic annotation for knowledge graph generation from text [23]. Applied domains benefiting from this approach include industry [3], [14], cybersecurity [2], biomedicine [1], criminal investigation [20], and social networks [6]. These approaches demonstrate the role of ontologies as semantic targets that ensure consistency and interoperability when structuring data from diverse and legacy systems.

C. Reproducibility Challenges in OBDG Literature

Despite methodological advancements, a critical examination of OBDG literature reveals persistent reproducibility challenges that hinder experimental validation and practical adoption. These challenges are not unique to OBDG but are also observed in related fields such as ontology reuse and synthesis [24], [25] and automatic annotation of scientific literature [13].

1) Incomplete Resource Access

Many studies provide only partial or no access to essential resources, including source code, datasets, and configuration details. For instance, systems such as OG-SGG [9] and DRAGON-AI [8] offer incomplete implementations with missing dependencies, while enterprise-scale approaches often become unavailable due to inactive download links [18].

2) Missing Dependencies and Outdated Documentation

Technical debt accumulates through outdated repositories, broken dependencies, and insufficient documentation. This significantly impedes system execution and adaptation, requiring extensive reverse engineering even when source code is available.

3) Non-Standardized Metrics and Task Variability

Performance evaluation lacks standardization, with studies employing diverse metrics, evaluation protocols, and task definitions. This variability complicates cross-approach comparison and hampers the establishment of reliable benchmarks for OBDG systems.

D. Synthesis of Existing Approaches and Accessibility

Our analysis of representative OBDG approaches reveals significant variability in resource accessibility, which directly impacts experimental reproducibility. Based on the availability of source code, datasets, and documentation, we classify systems into three categories: *Full* (complete and functional resources), *Partial* (limited or incomplete resources), and *Unavailable* (critical resources are inaccessible).

Among the systems examined, only **DataBot** [16], a conversational interface for tabular data analysis, qualifies as fully accessible, providing complete source code, datasets, and documentation that enable direct replication.

Several systems offer only partial accessibility. **OG-SGG** [9], designed for ontology-guided scene graph generation in robotics and computer vision, provides incomplete code and outdated files. **DRAGON-AI** [8], which leverages LLMs for dynamic ontology generation, lacks essential dependencies and configuration files. Similarly, **Domain Ontology-Driven Knowledge Graph Generation** [23] provides partial code and datasets, and **Ontology-Based Data Access** [26] relies on outdated libraries and non-functional scripts.

Notably, some systems are entirely unavailable for replication. **Ontology-Based Data Platform Assets** [18], targeting enterprise-scale data asset generation, has inactive download links. Likewise, **Ontology-Based Annotation for Genomic Data** [1] is hosted in a repository that is no longer accessible.

This accessibility landscape underscores the reproducibility gap in current OBDG research. The predominance of partially accessible or unavailable systems hinders independent validation, cross-system comparison, and cumulative scientific progress. These findings motivate the need for standardized practices and improved resource sharing.

Several initiatives have established guidelines for research transparency. The FAIR principles [24] emphasize data findability, while organizations like ACM and conferences like NeurIPS provide checklists for code and ML reproducibility. However, these standards are often too general for the specific semantic requirements of OBDG. Our framework addresses this gap by providing domain-specific guidance.

Current literature reveals three primary limitations in existing OBDG research. First, there is inconsistent resource accessibility, with many systems providing only partial or no access to essential components [9]. Second, evaluation methodologies lack standardization, employing diverse metrics and protocols that complicate fair comparison [11], [16], [20]. Third, there is insufficient attention to generalizability testing, with most studies focusing narrowly on specific domains without assessing cross-domain applicability [22]. These limitations collectively hinder the cumulative progress and practical deployment of OBDG technologies.

Table I provides a structured comparison between our proposed framework and existing prominent standards to highlight our contributions.

TABLE I
COMPARISON OF THE PROPOSED FRAMEWORK WITH EXISTING STANDARDS

Standard	Primary Focus	Contrast with Our Approach
FAIR Principles	Metadata findability and long-term data reuse.	Emphasizes static data assets rather than technical execution protocol.
NeurIPS/ACM	General reproducibility checklists for ML and code.	Domain-agnostic; lacks checks for semantic consistency (TBox/ABox).
Our Framework	**Technical and semantic validation of OBDG.**	**Integrates performance comparability and cross-domain generalizability.**

III. Proposed Reproducibility Assessment Framework

To address the reproducibility challenges identified in Section II, we propose a structured four-step assessment protocol. This framework is designed to systematically evaluate the reproducibility of ontology-based data generation (OBDG) systems, promote transparent reporting, and facilitate comparative analysis across different approaches.

A. Four-Step Assessment Protocol

The protocol comprises four sequential steps, each focusing on a critical aspect of reproducibility. Figure 1 provides a visual overview of the complete assessment process.

1) Step 1: Accessibility Assessment

This step evaluates the availability of essential resources required to replicate the system. We assess the presence of code repositories, configuration files, environment specifications, and ontology artifacts. We define three levels of accessibility:

- **Full:** Complete source code, datasets, configuration files, and documentation are publicly available and functional.
- **Partial:** Some resources are available but with limitations (e.g., incomplete code, missing dependencies, outdated files).
- **Unavailable:** Critical resources are inaccessible (e.g., inactive links, private repositories).

Accessibility is a prerequisite for experimental replication and must be clearly reported in publications. The framework quantifies this dimension through a reproducibility score.

2) Step 2: Executability Verification

Once resources are accessible, this step assesses the technical feasibility of executing the system. Key verification points include:

- Dependency resolution and environment setup (e.g., via Docker, conda).
- Successful build and compilation without errors.
- Runtime functionality on standard hardware and software platforms.

Systems that pass this step are considered *executable* and can proceed to performance evaluation. Failures typically involve missing dependencies, build errors, or platform incompatibilities.

3) Step 3: Performance Comparability

This step compares reproduced results with originally reported performance metrics using standardized measures. We recommend precision, recall, and F1-score for classification and extraction tasks, as they are widely adopted in NLP and AI evaluation. Additional domain-specific metrics may be included but must be clearly defined. Discrepancies between

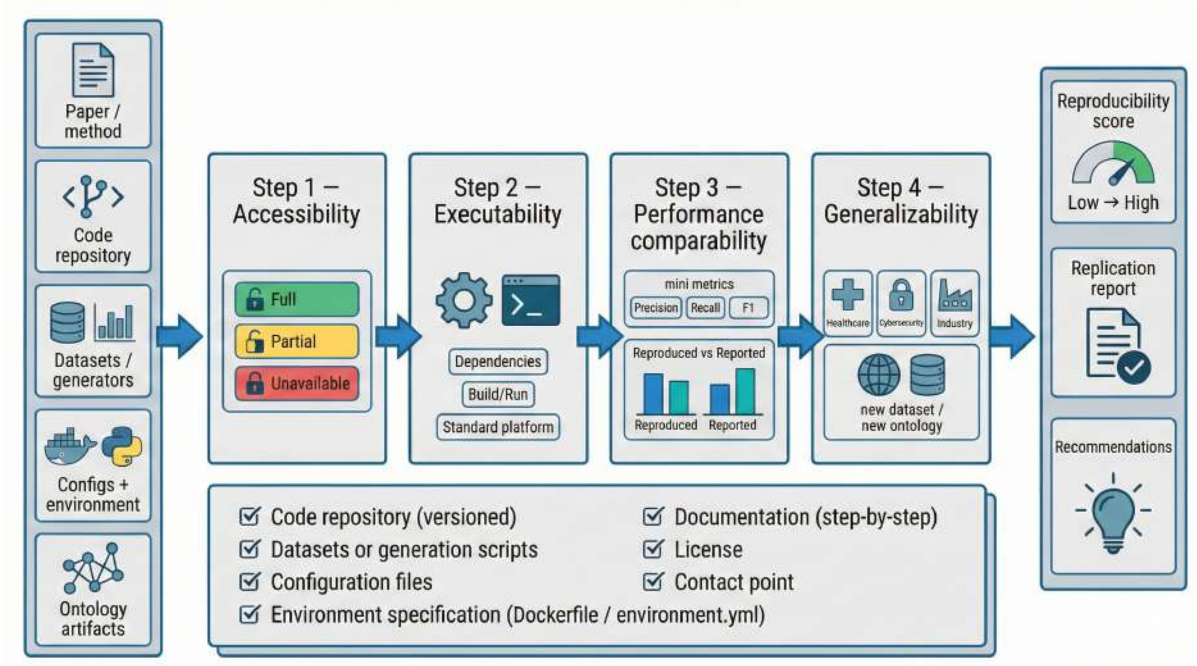

Fig. 1. Four-step reproducibility assessment framework for ontology-based data generation systems. The process begins with accessibility evaluation, progresses through executability verification and performance comparability, and concludes with generalizability testing across multiple domains.

original and reproduced results should be systematically analyzed and documented.

4) *Step 4: Generalizability Testing*

The final step evaluates the robustness and adaptability of the system by testing its performance across multiple domains, datasets, or ontological structures. This assesses whether the approach can be successfully applied beyond the specific context of the original study. Our framework specifically tests generalizability across key domains such as healthcare, cybersecurity, and industry applications, which represent primary use cases for OBDG systems.

B. *Checklist for Authors*

To promote reproducibility and facilitate application of our assessment protocol, we propose the following checklist for authors of OBDG studies:

- **Code Repository:** Publicly accessible repository (GitHub, GitLab) with version control.
- **Datasets:** Direct access to datasets or scripts for generating synthetic data.
- **Configuration Files:** Complete configuration files for all experiments.
- **Environment Specification:** Detailed setup instructions (Dockerfile, conda environment.yml).
- **Documentation:** Step-by-step instructions for installation, execution, and result replication.
- **License:** Clear licensing terms for code and data.
- **Contact Point:** Designated contact for replication questions.

Adoption of this checklist by authors, reviewers, and conferences would significantly enhance transparency and reproducibility in OBDG research.

IV. Case Study: Applying the Framework

To validate the practical utility of our reproducibility assessment framework, we applied it to two representative OBDG systems: *DataBot* [16], a conversational interface for tabular data analysis, and *OG-SGG* [9], an ontology-guided scene graph generation system for robotics. These systems were selected based on their differing accessibility levels and application domains.

A. *Experimental Setup*

For each system, we followed the four-step protocol outlined in Section III-A. The evaluation was conducted on Ubuntu 22.04 with 32GB RAM and NVIDIA RTX 3080 to ensure consistency. We documented all steps, including dependency installation, configuration adjustments, and execution attempts. When original datasets were unavailable, we used compatible alternatives or generated synthetic data following the authors' descriptions.

B. *Results*

1) *DataBot*

DataBot achieved a *Full* accessibility rating, as all resources (code, datasets, configurations) were publicly available and well-documented. The system passed executability verification without major issues, requiring only standard Python library installations.

Performance comparability was assessed using intent classification tasks. As shown in Table II, the reproduced results closely matched the originally reported metrics, with an overall accuracy of 69%. However, we observed variance in precision and recall across intent categories. Well-defined intents (e.g., `max_value`, `value_frequency`) achieved near-perfect scores, while ambiguous intents (e.g., `bar_chart`, `pie_chart`) exhibited lower precision.

TABLE II
REPRODUCED INTENT CLASSIFICATION RESULTS FOR DATABOT

Intent	Precision	Recall	F1-score
bar_chart	0.50	1.00	0.67
line_chart	0.67	1.00	0.80
max_value	1.00	1.00	1.00
min_value	1.00	0.67	0.80
pie_chart	0.50	1.00	0.67
select_fields_with_conditions	1.00	0.50	0.67
show_table	0.50	1.00	0.67
value_frequency	1.00	1.00	1.00
Overall Accuracy		0.69	

Generalizability testing was performed on a financial tables dataset, where DataBot maintained consistent performance for aggregation-related intents but struggled with domain-specific terminology not present in the original training data. This highlights the importance of domain adaptation in ontology-based conversational systems.

2) OG-SGG

OG-SGG received a *Partial* accessibility rating due to incomplete code and missing dependencies. We successfully executed a simplified version after supplementing missing components with custom implementations based on the paper's description. Performance comparability was limited by the absence of the original evaluation dataset. Using the COCO dataset, we achieved a scene graph generation F1-score of 0.62, compared to the reported 0.71 in the original paper.

This observed discrepancy highlights a critical aspect of OBDG reproducibility. Rather than a failure to replicate, this variation stems from the domain shift involved in applying the framework to the MS-COCO dataset. While the core logic of the ontology remained consistent, the alignment between the TBox (conceptual layer) and the diverse visual instances in MS-COCO introduced semantic noise not present in the original controlled environment. This result underscores the necessity of our "Generalizability" step, proving that OBDG performance is deeply tied to the underlying data distribution and mapping precision.

However, the system demonstrated improved semantic consistency over non-ontology-based baselines, validating the benefits of ontological guidance. Generalizability testing across different visual domains (e.g., indoor scenes, vehicular environments) revealed that OG-SGG's performance degraded when the target domain's visual concepts diverged significantly from the training ontology. This underscores the dependency of ontology-guided systems on well-aligned domain models.

C. Key Findings

The application of our framework yielded several important insights:

- **Accessibility directly impacts reproducibility:** Systems with full accessibility enabled precise replication and reliable evaluation. Partial accessibility necessitated adaptations that introduced variability.
- **Ontology alignment is critical:** Systems performed best when the ontology accurately represented the target domain.
- **Standardized metrics facilitate comparison:** Using precision, recall, and F1-score enabled consistent evaluation across domains.
- **Generalizability requires careful design:** Modular ontological structures demonstrated better cross-domain adaptability than tightly coupled approaches.
- **Data quality impacts reproducibility:** Rare or ambiguous classes showed the weakest performance.

These findings validate the practical relevance of our reproducibility assessment framework.

V. DISCUSSION AND IMPLICATIONS

Our framework provides several distinct advantages over existing approaches. Traditional reproducibility standards like FAIR principles focus on data publication but lack structured protocols for assessing OBDG system replication. Unlike survey works that merely catalog reproducibility issues, our framework provides actionable assessment steps and a concrete checklist. Compared to domain-specific evaluation methodologies in biomedical ontologies or cybersecurity knowledge graphs, our approach offers cross-domain applicability.

The four-step protocol advances beyond previous efforts by: (1) graduating accessibility assessment from binary classification; (2) integrating technical executability with semantic performance comparison; (3) explicitly addressing cross-domain generalizability; and (4) providing practical implementation guidelines.

A. Implications for Stakeholders

For researchers, our framework provides structured assessment approaches and practical resource-sharing guidelines. For conference committees, this work suggests reproducibility should be a key evaluation criterion. For industry practitioners, the framework offers a validation protocol to assess system robustness before deployment.

B. Limitations

Several limitations must be acknowledged. Our case study focused on two systems, limiting specific generalizability. The framework's effectiveness depends on compatible alternative datasets availability. Ontology design variations complicate cross-system comparisons. The framework currently requires manual implementation.

Despite these limitations, our work establishes a foundation for more reproducible OBDG research. Future efforts should expand the application to broader systems and develop automated assessment tools.

VI. CONCLUSION AND FUTURE DIRECTIONS

This paper addressed the critical challenge of reproducibility in Ontology-Based Data Generation (OBDG) by proposing a structured, four-step assessment framework covering accessibility, executability, comparability, and generalizability. Through empirical validation via case studies in conversational AI and robotics, we demonstrated how our protocol successfully systematically identifies and categorizes barriers in technical and semantic replication packages.

To establish a rigorous, evidence-based foundation for reproducibility in OBDG research and accelerate the development of robust, scalable, and trustworthy ontology-based data generation systems, future work will focus on the following directions:

1) **Systematic Registry Expansion:** Formalize a comprehensive repository of audited frameworks with precise access dates and explicit inclusion/exclusion criteria to ground broad claims about OBDG resource accessibility.
2) **Extended Case Studies:** Apply the framework to 5–8 diverse OBDG systems across healthcare, cybersecurity, and industrial domains to thoroughly validate cross-domain generalizability and establish clear performance benchmarks.
3) **Empirical Checklist Impact:** Survey and track authors who adopt the proposed practical checklist to measure its real-world impact on reproducibility outcomes and refine the guidelines based on implementation feedback.
4) **Automation and Tooling:** Develop automated assessment tools and discovery scripts that detect accessibility levels, verify environment dependency resolution, and compute quantitative reproducibility scores to transition from manual expert assessment to an objective, scalable audit pipeline.
5) **Hybrid and Multimodal Extensions:** Explore ontology-guided approaches combining symbolic reasoning with large language models, and extend the reproducibility assessment framework to multilingual and multimodal OBDG applications.

By addressing these research directions, we can bridge the gap between ontology design and technical execution, providing a foundation for more reliable, scalable, and transparent semantic data systems across healthcare, cybersecurity, industry, and beyond.

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