
Large Language Models for Ontology Engineering: A Systematic Literature Review

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Abstract

Ontology engineering (OE) is a complex task in knowledge representation that relies heavily on domain experts to accurately define concepts and precise relationships in a domain of interest, as well as to maintain logical consistency throughout the resultant ontology. Recent advancements in Large Language Models (LLMs) have created new opportunities to automate and enhance various stages of ontology development. This paper presents a systematic literature review on the use of LLMs in OE, focusing on their roles in core development activities, input-output characteristics, evaluation methods, and application domains. We analyze 30 different papers to identify common tasks where LLMs have been applied, such as ontology requirements specification, implementation, publication, and maintenance. Our findings indicate that LLMs serve primarily as auxiliary ontology engineers, domain experts, and evaluators, using models such as GPT, LLaMA, and T5 models. Different approaches use zero and few shot prompt techniques to process heterogeneous inputs (such as OWL ontologies, text, competency questions, etc.) to generate task-specific outputs (such as examples, axioms, documentation, etc.). Our review also observed a lack of homogenization in task definitions, dataset selection, evaluation metrics, and experimental workflows. At the same time, some papers do not release complete evaluation protocols or code, making their results hard to reproduce and their methods insufficiently transparent. Therefore, the development of standardized benchmarks and hybrid workflows that integrate LLM automation with human expertise will become an important challenge for future research.

Keywords

Large Language Models, Ontology Engineering, Ontology Development, Systematic Review Survey

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1 Introduction

For more than a decade, Knowledge graphs (KGs) have become a key technology to represent, use, and share open knowledge in a wide range of domains and applications [Hogan et al. \(2021\)](#). To give these rich datasets formal machine-readable structure and semantics [Patel and Debnath \(2024\)](#); [Glauer et al. \(2024\)](#), ontologies are employed to define domain-specific concepts, relationships, constraints and logical rules [De Vergara et al. \(2004\)](#); [Patel and Debnath \(2024\)](#); [Glauer et al. \(2024\)](#). Ontologies are typically encoded in the W3C Web Ontology Language (OWL) [Staab et al. \(2004\)](#), and have been shown to work effectively to integrate, validate, and reason with data in KGs [Krötzsch and Thost \(2016\)](#).

Ontology Engineering (OE) is the process of developing formal knowledge representations (i.e., ontologies) to describe aspects of reality for specific purposes [Salamon and Barcellos \(2022\)](#). Despite the availability of structured methodologies such as Linked Open Terms (LOT) [Poveda-Villalón et al. \(2022\)](#), NeOn [Suárez-Figueroa et al. \(2012\)](#), the “Ontology Development 101” guide [Noy and McGuinness \(2001\)](#), etc., ontology development remains a complex, time-consuming, and error-prone activity [Gangemi and Presutti \(2009\)](#); [Saeedizade and Blomqvist \(2024\)](#). It demands deep domain expertise, careful conceptual modeling, extensive collaboration among stakeholders, and precise alignment with intended use cases.

With the development of Artificial Intelligence (AI), significant advancements have been made in Large Language Models (LLMs) to show remarkable advances in capturing complex language patterns in different knowledge domains [Doumanas et al. \(2024\)](#). In recent years, LLMs have emerged as an innovative technology for OE. Research efforts have explored their potential to assist developers in various tasks, including generating and refining ontologies from text, aligning concepts with existing taxonomies, and automatically detecting syntax errors in ontologies, among others [Garijo et al. \(2024\)](#).

Despite the promise of LLMs for OE, several key research gaps remain. Many studies have claimed that LLMs are useful for ontology development tasks [Lo et al. \(2024\)](#); [Joachimiak et al. \(2024\)](#); [Lippolis et al. \(2025, 2024\)](#); [Ciatto et al. \(2025\)](#), but do not clearly distinguish the specific development phases where LLMs provide the most value. In addition, little is known about the specific roles LLMs can assume, the types of inputs and outputs required by them, the need and extent of human involvement, and the experimental setups, including datasets used, evaluation metrics, and reproducibility considerations used to validate their effectiveness. Furthermore, while LLMs are increasingly applied in various domains, few studies systematically address domain-specific challenges or necessary model adaptations. Although recent surveys have offered valuable overviews of LLMs in OE [Perera and Liu \(2024\)](#); [Garijo et al. \(2024\)](#), a detailed analysis focusing specifically on ontology development activities remains limited. A systematic understanding of how LLMs contribute to different phases of ontology development, along with a critical assessment of their capabilities and limitations, is essential for guiding future research and fostering their successful integration into OE workflows.

To address these gaps, this study conducts a comprehensive and systematic review of how LLMs are employed in OE. We extend the overview presented in our previous work [Garijo et al. \(2024\)](#) with the following contributions: First, through a comprehensive systematic search, we broaden and update the literature coverage, ultimately identifying 30 peer-reviewed papers published between 2018 and 2024, significantly more than the 20+ papers included in the earlier overview. Second, we introduce a structured analytical framework that categorizes existing research according to ontology engineering stages, LLM roles, LLM technical details, and input/output formats for and from each LLM. Third, we examine dataset usage, evaluation practices, and the degree of human involvement in LLM-supported workflows. Finally, we analyze the application domains in which LLMs have been deployed for ontology development,

offering additional cross-study insights. Building on these contributions, this extended study aims to achieve the following objectives:

1. Identify the ontology development tasks where LLMs have been applied.
2. Analyze how LLM-based approaches contribute to ontology development, focusing on their roles, model types, inputs, outputs, and the role of human participants in interactive workflows.
3. Examine how LLM performance is assessed in ontology development by identifying experimental datasets, evaluation methods, and reported performance results.
4. Explore the application domains where LLMs have been effectively utilized for ontology development.

We conduct our review following the systematic methodology proposed by Kitchenham et al. [Kitchenham et al. \(2009\)](#), ensuring a rigorous and reproducible analysis. We also make publicly available the complete corpus of resources used to generate or evaluate different OE tasks at our GitHub repository.¹ In addition, the corpus is archived on Zenodo [Li et al. \(2025\)](#).

The remainder of this article is organized as follows. Section 2 presents background information on OE and LLM technologies. Section 3 outlines our research objectives and key questions, and describes the data collection and analysis methods. Section 4 presents the research results and the key insights. Section 5 shows the discussion from the analyzed studies, and Section 6 concludes the survey by highlighting open research challenges. Finally, Section 7 describes supporting materials used in our work.

2 Background

In this section, we briefly introduce the main ontology development tasks identified in the literature and provide an overview of the recent evolution of LLMs.

2.1 Ontology Development Tasks

Ontologies are formal and explicit specifications of shared conceptualizations [Studer et al. \(1998\)](#), enabling structured knowledge representation [Dimitropoulos and Hatzilygeroudis \(2024\)](#) and facilitating semantic interoperability across systems and applications [Bittner et al. \(2005\)](#); [Tan et al. \(2024\)](#).

Ontology engineering (OE) provides the methodologies and tools necessary to construct domain-specific and application-specific ontological models [Gómez-Pérez \(1999\)](#). An Ontology Engineering Methodology (OEM) outlines a structured set of phases, processes, and tasks to systematically guide the development process [Kotis et al. \(2020\)](#).

Traditional methodologies, such as METHONTOLOGY [Fernández-López et al. \(1997\)](#), On-To-Knowledge [Staab et al. \(2001\)](#), DILIGENT [Pinto et al. \(2004\)](#), and the “Ontology Development 101” guide [Noy and McGuinness \(2001\)](#), have significantly contributed to the formalization of OE practices. However, they typically follow step-by-step workflows that may not fully address modern requirements such as reuse, collaboration, and interoperability. The NeOn methodology [Suárez-Figueroa et al. \(2012\)](#)

¹<https://github.com/oeg-upm/llm4oe-sl1>

introduced a more dynamic and flexible approach, emphasizing the creation of interconnected ontology networks through mechanisms like import, versioning, mapping, and modularization.

To consider a basic group of activities usually carried out during ontology development we follow the Linked Open Terms (LOT) methodology [Poveda-Villalón et al. \(2022\)](#) general workflow as it includes ontology publication and maintenance phases. However, other activities not defined in detail in LOT may appear in the reviewed works. In order to address these cases we also consider the NeOn glossary of activities [Suárez-Figueroa and Gómez-Pérez \(2008\)](#). It should be noted that both LOT and NeOn define more activities than the ones listed below, however, we include in this section only those activities found in the reviewed papers.

1. Ontology requirements specification phase: Gathering requirements is related to the specific ontology goals, domain, and technical constraints [Suárez-Figueroa et al. \(2009\)](#). From the activities defined for this phase, in the analyzed papers the following activities are addressed:

- *Functional requirements writing:* Specifies the functionalities the ontology must support. It should be noted that this activity refers to writing the functional requirements in natural language text. This may occur in the form of competency questions or affirmative sentences in natural language.
- *Competency question reverse engineering:* Involves generating CQs that an ontology must answer, using the ontology itself as input. Although not explicitly covered in the LOT framework, this activity appears in several studies ([Alharbi et al. \(2024a\)](#)) and aligns with NeOn Ontological Resource Reverse Re-engineering [Suárez-Figueroa et al. \(2012\)](#).
- *Requirement formalization:* This activity consists in translating functional requirements into formal, machine-readable specifications.

2. Ontology implementation phase: Building the ontology using formal languages (e.g., OWL, RDF) based on collected requirements. Key sub-activities include:

- *Conceptualization:* Structuring domain knowledge into concepts and relationships.
- *Encoding:* Formalizing conceptual models into machine-readable formats (e.g., Turtle, RDF/XML, etc.).
- *Evaluation:* Validating the ontology against competency questions and domain needs.
- *Matching:* This activity's definition is taken from NeOn which literally reads “the activity of finding or discovering relationships or correspondences between entities of different ontologies or ontology modules” [Suárez-Figueroa and Gómez-Pérez \(2008\)](#).

3. Ontology publication phase: Making the ontology accessible both as human-readable documentation and machine-readable files. This phase includes, among others not found in the reviewed papers as the actual online publication, the following activity:

- *Documentation:* Generating human-oriented documentation usually consisting, but not limited to HTML web pages, diagrams, examples of use, etc.

4. Ontology maintenance phase: Updating the ontology based on bug reports, improvements, and new requirements throughout its lifecycle. This includes:

- *Bug detection*: Identifying and reporting errors or inconsistencies.

2.2 A Brief History of Large Language Models

LLMs are AI systems able to generate coherent and contextually relevant language outputs that have demonstrated remarkable performance across tasks like text generation [Mishra et al. \(2025\)](#); [Wu \(2024\)](#), question answering [Arefeen et al. \(2024\)](#); [Balepur et al. \(2025\)](#), translation [Brown et al. \(2020\)](#), summarization [Azher et al. \(2025\)](#), and sentiment analysis [Kheiri and Karimi \(2024\)](#). LLMs are trained on large amounts of textual data, and are built predominantly on deep learning architectures such as transformers [Vaswani et al. \(2017\)](#).

The evolution of LLMs began with foundational advancements in sequential data processing. Rumelhart et al. [Rumelhart et al. \(1986\)](#) introduced recurrent neural networks (RNNs), which were later enhanced by the Long Short-Term Memory (LSTM) model developed by Hochreiter and Schmidhuber [Hochreiter and Schmidhuber \(1997\)](#), significantly improving long-range dependency modeling [Mienye et al. \(2024\)](#). The release of the Generative Pre-trained Transformer (GPT) by OpenAI in 2018 marked a pivotal moment. Subsequent iterations (GPT-2, GPT-3, GPT-3.5) demonstrated increasingly sophisticated generative capabilities [Brown et al. \(2020\)](#); [Radford et al. \(2019\)](#). GPT-3, for instance, was trained on 45TB of data and contained 175 billion parameters. In 2023, Meta introduced LLaMA, an open-source LLM trained on 1.4 trillion tokens across multiple model sizes [Raiaan et al. \(2024\)](#). Since then, models such as Google Gemini Team et al. [\(2024\)](#), OpenAI's GPT-4 [OpenAI et al. \(2024\)](#), Meta LLaMA2 [Touvron et al. \(2023b\)](#), and LLaMA3 [Grattafiori et al. \(2024\)](#) have further advanced the field. These models exhibit state-of-the-art performance in reasoning [Wei et al. \(2022\)](#), code generation [Vaithilingam et al. \(2022\)](#); [Jiang et al. \(2024\)](#), and multimodal tasks [Zhang et al. \(2023b\)](#); [Wu et al. \(2023\)](#); [Zhang et al. \(2024a\)](#), driven by larger datasets and increasingly sophisticated architectures. Their ongoing evolution continues to expand the application landscape for AI-driven systems across diverse domains [Johnsen \(2025\)](#).

Prompt engineering has emerged as a key methodology for enhancing the performance of pre-trained LLMs [Debnath et al. \(2025\)](#). It involves the careful design of instructions, conveyed through text, images, audio, or other modalities, that serve as the primary interface to guide LLMs in downstream tasks [Marvin et al. \(2023\)](#). A wide variety of prompting strategies have been developed to steer models toward accurate and contextually appropriate outputs. For example, zero-shot prompting is based exclusively on a task description, allowing models to generalize to unseen tasks without any examples [Radford et al. \(2019\)](#). In contrast, one-shot [Kojima et al. \(2022\)](#) and few-shot [Brown et al. \(2020\)](#) prompting incorporate one or several demonstrations, helping the model better infer input–output relationships [Kadam and Vaidya \(2018\)](#).

Other techniques aim to improve the structure and consistency of model outputs. Role prompting [Zheng et al. \(2024\)](#); [Olea et al. \(2024\)](#) assigns the model a specific persona or professional role, thus shaping its reasoning style and lexical choices. Template-based prompting [Shin et al. \(2020\)](#) employs predefined templates populated with task-specific variables to enforce structured formats such as JSON, tables, or logical expressions.

Chain-of-Thought (CoT) prompting [Wei et al. \(2022\)](#) augments few-shot learning by guiding models to articulate intermediate reasoning steps before delivering final answers. Also referred to as Chain-of-Thoughts in some studies [Besta et al. \(2024\)](#); [Chen et al. \(2023\)](#), this approach has been shown to substantially enhance LLM performance in mathematical and reasoning tasks. Typical CoT prompts include exemplar questions paired with reasoning traces and correct answers. The Reasoning and Acting

(ReAct) framework [Yao et al. \(2022\)](#) extends CoT by interleaving reasoning with executable actions. When solving a problem, the model iteratively generates a thought, takes an action, and observes the outcome, maintaining a contextual memory by incorporating past reasoning steps, actions, and observations into the prompt. Further advancing multi-step reasoning, self-consistency sampling enhances output reliability by selecting the most consistent answer from multiple reasoning trajectories. Building on these foundations, frameworks such as ReAct [Yao et al. \(2022\)](#) and Tree-of-Thought (ToT) [Yao et al. \(2023\)](#) integrate systematic reasoning with action execution or structured search, supporting more sophisticated decision-making processes.

Fine-tuning is a process in which a pretrained model, such as an LLM, is further trained on a custom data set to adapt it for specialized tasks or domains. Complementing prompt-based approaches, fine-tuning provides a parameter-level adaptation mechanism that aligns LLMs with specific domains or tasks [Anisuzzaman et al. \(2024\)](#). Methods such as instruction tuning [Zhang et al. \(2023a\)](#), domain-specific fine-tuning [Gajulamandyam et al. \(2025\)](#), and parameter-efficient [Liu et al. \(2022\)](#) approaches such as LoRA [Hu et al. \(2022\)](#) or adapter tuning [Le et al. \(2021\)](#) enable models to internalize task patterns beyond the reach of prompts alone. Fine-tuning enhances output stability, mitigates prompt sensitivity, and ensures consistent performance in scenarios that require specialized knowledge or complex reasoning.

Overall, prompting techniques have evolved into a flexible and reusable interaction layer that complements advances in LLM architectures. By enabling more accurate, controllable, and domain-aligned outputs, prompt engineering has become central to the effective deployment of LLMs, serving as a key driver of innovation across AI applications.

3 Research Methodology

To achieve our research objectives, we conducted a systematic literature review following Kitchenham and Charters methodology [Kitchenham et al. \(2009\)](#): Section 3.1 defines the research questions (RQs) of our study, Section 3.2 describes the selection of data sources, Section 3.3 presents the search strategy, Section 3.4 explains the filtering criteria, and Section 3.5 details data extraction and synthesis. The following subsections describe each step.

3.1 Research Questions

Our study investigates how LLMs have been adapted for ontology development by systematically reviewing existing approaches to understand their capabilities and limitations. We formulate the following RQs to guide our review:

RQ1 What are the key activities in ontology development where LLMs have been applied?

RQ2 How do LLM-based approaches support different ontology development activities?

RQ2.a What roles do LLMs play in these activities?

RQ2.b What types of LLMs are used?

RQ2.c What LLM prompt techniques are employed to support OE activities (e.g., zero-shot prompt, iterative prompt, fine-tuning)?

RQ2.d What are the typical inputs to the LLMs?

RQ2.e What outputs are generated by the LLMs?

RQ2.f What are the roles of humans involved in these activities (e.g., domain experts, ontology engineers)?

RQ3 How is the performance of LLMs in ontology development evaluated?

RQ3.a Are there evaluation experiments reported?

RQ3.b What datasets are used in the evaluations?

RQ3.c What evaluation methods are adopted (e.g., qualitative, quantitative, or hybrid)?

RQ3.d What metrics (e.g., F1 score, recall) are used, and what are the reported performance results?

RQ4 What are the main application domains where LLMs have been applied in ontology development?

3.2 Source Libraries

During this phase, we conduct a systematic search across open-access digital libraries to ensure comprehensive coverage of the area under investigation Vieira and Gomes (2009). We selected Google Scholar, Web of Science, and Scopus for their broad multidisciplinary reach, along with the ACM Digital Library and IEEE Xplore to specifically cover the computer science domain Hull et al. (2008). The selected sources and their corresponding access points are: **Google Scholar**², **Web of Science**³, **Scopus**⁴, **ACM Digital Library**⁵, and **IEEE Xplore**⁶.

3.3 Search Strategy

The selection of primary studies depend on the following inclusion and exclusion criteria:

1. **Publication Time Frame:** We focus on papers published between 2018 and 2024 to capture the most recent advances in ontology development driven by large language models (LLMs). The year 2018 marks a pivotal milestone in NLP, corresponding to the introduction of the Transformer architecture and the release of foundational models such as BERT Devlin et al. (2019) and GPT Radford and Narasimhan (2018), which laid the groundwork for the modern LLM paradigm.
2. **Peer-Review Status:** Selecting peer-reviewed papers ensures rigorous expert evaluation, enhancing the high quality, credibility, and reliability of our findings Kelly et al. (2014).
3. **Language:** We focus on papers, books, and book chapters published in English for accessibility and consistency.
4. **Search Keywords:** Our search focuses on two categories of terms:

²<https://scholar.google.com>

³<https://www.webofscience.com>

⁴<https://www.scopus.com>

⁵<https://dl.acm.org>

⁶<https://ieeexplore.ieee.org>

- (a) Semantic-Related Terms (SR): Keywords related to semantic technologies, such as ontolog*, ontology development, and vocabulary.
- (b) Model-Related Terms (MR): Keywords associated with large language models, including Language Model, LM, and LLM*.

The particularities of each source were considered during the review. Logical operators (OR, AND) combined terms into search strings, such as ('ontolog*' OR 'ontology development') AND ('LM' OR 'LLM*'), applied to meta-fields searched from Section 3.2. Depending on each source, the search strings were tailored to content, title, abstract, and keywords.

3.4 Filtering Process

In this step, we apply our search criteria to the selected library sources through a two-stage filtering process.

1. **Automated Filtering:** We first applied automated filters based on the predefined search standards and removed duplicate papers by matching their titles.
2. **Manual Filtering:** To further ensure relevance, we conducted a multi-stage manual review, comprising the following steps:
 - (a) **Title Screening:** We initially reviewed the titles of the retrieved papers to eliminate papers that were clearly unrelated to our research topic.
 - (b) **Abstract Screening:** For the remaining papers, we examined the abstracts to assess their alignment with our research objectives. Only peer-reviewed papers that explicitly addressed the role of LLMs in ontology development were retained.

3.5 Data Extraction

To extract relevant information, we aligned the data extraction process with the RQs defined in Section 3.1. Since a single article may involve multiple ontology development activity experiments, each activity was recorded as a separate row in the dataset. The complete dataset is publicly available in our open repository at <https://github.com/oeg-upm/llm4oe-slr>.

Specifically, we extracted the following information from each entry:

- **Article metadata:** Publication title, authors, publication year, peer-reviewed status, and language.
- **Ontology Activity (RQ1):** The ontology development activity supported by LLMs and its definition (if provided).
- **LLM Technology (RQ2):** Role of the LLM in the activity, type of LLM used, technique of prompt used, inputs provided to the LLM, outputs generated, whether human-in-the-loop involvement was present (Yes/No), role of the human (e.g., ontology engineers and others), and tasks performed by human participants.

- **Performance Evaluation (RQ3):** Existence of evaluation experiments, links to experiments (if available), datasets used, dataset types, baselines compared, evaluation methods (quantitative, qualitative, or hybrid), metrics applied (e.g., F1 score, recall), and performance results, including whether humans participated in the evaluation.
- **Application Domains (RQ4):** Domains where LLMs were applied, such as healthcare, education, and finance.

4 Search Results

Our initial search yielded 11,985 results, which were reduced to 5,275 unique papers after duplicate removal. The title selection narrowed this set to 204 papers, and the subsequent abstract selection further shortlisted 38 peer-reviewed papers related to the use of LLMs in OE. From these 38 shortlisted papers, we excluded 2 review articles Garijo et al. (2024); Perera and Liu (2024) and 6 studies that primarily focused on the extraction of knowledge or ontology population rather than the design or structural development of the ontology itself Usmanova and Usbeck (2024); Mukanova et al. (2024); Sahbi et al. (2024); Tian et al. (2023); Funk et al. (2023). Consequently, the 30 core studies were retained for the final analysis, as illustrated in Figure 1. These 30 studies form the foundation for the systematic investigation presented in the remainder of this paper.

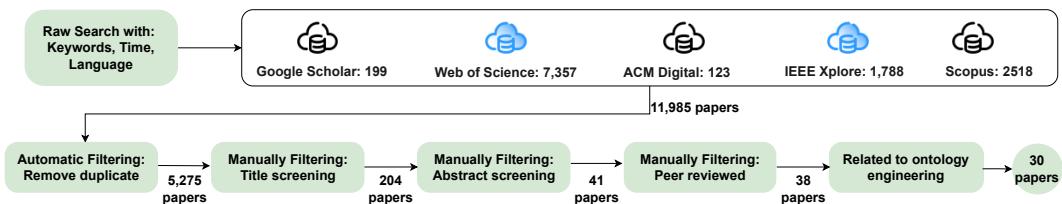


Figure 1. Paper selection process based on our methodology. From 11,985 papers retrieved across five libraries, 30 papers related to our LLM-based OE tasks were selected after duplicate removal and manual filtering.

Figure 2³ supported provides a summary of our results by grouping existing works by OE task, input and output. The diagram integrates all tasks identified in the selected studies and organizes them according to the four main OE phases: ontology requirements specification, ontology implementation, ontology publication, and ontology maintenance. It also indicates the key aspects examined in our four research questions, including LLM inputs and outputs, model types, prompting strategies, human participation, functional roles of LLMs, and the availability of evaluation and datasets used across the 41 reported

⁷The figure groups tasks by OE phases and summarizes LLM models, prompting strategies, and human roles. Rounded rectangles denote LLM inputs (e.g., natural language text (NL text), CQs, ontologies) and outputs, while icons indicate human involvement and the availability of experiments or datasets.

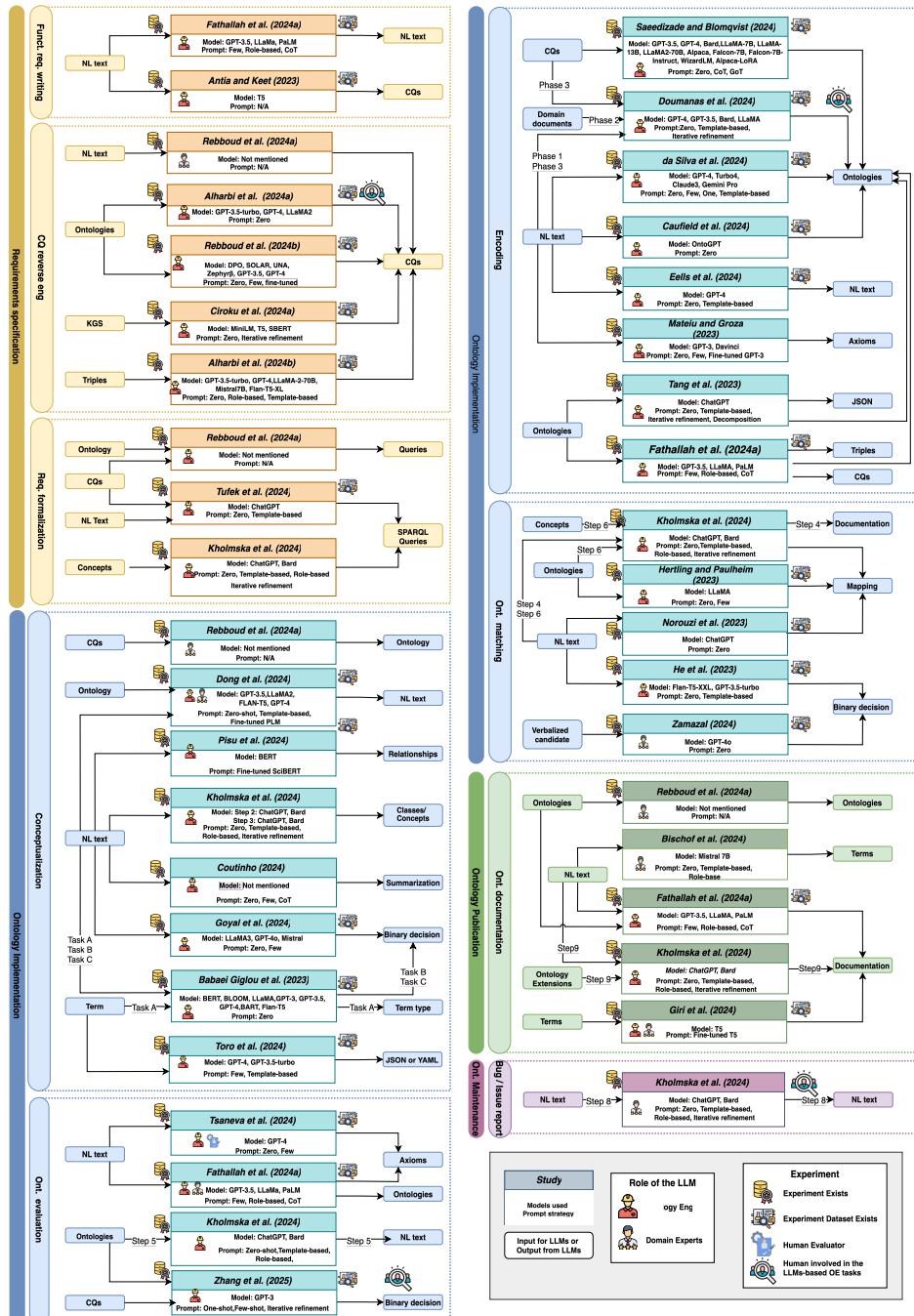


Figure 2. Overview of LLM-supported ontology engineering tasks based on 41 experiments from 30 papers.⁷

experiments. Building on this overview, the following subsections present detailed results for each research question.

4.1 RQ1: What are the key activities in ontology development where LLMs have been applied?

The first step in our study is to analyze in which ontology engineering activities are LLMs applied. Table 1 compiles the activities addressed in each of the analyzed approaches including the input and outputs provided to the LLM for each activity. A paper may address more than one ontology development activity, and therefore the same paper may lead to multiple rows in the table. As shown in Figure 3, most of the attention is focused on activities related to ontology implementation tasks (encoding, conceptualization, matching or evaluation) as well as the generation of requirements. Each approach is summarized in the following section grouping them by OE activity addressed.

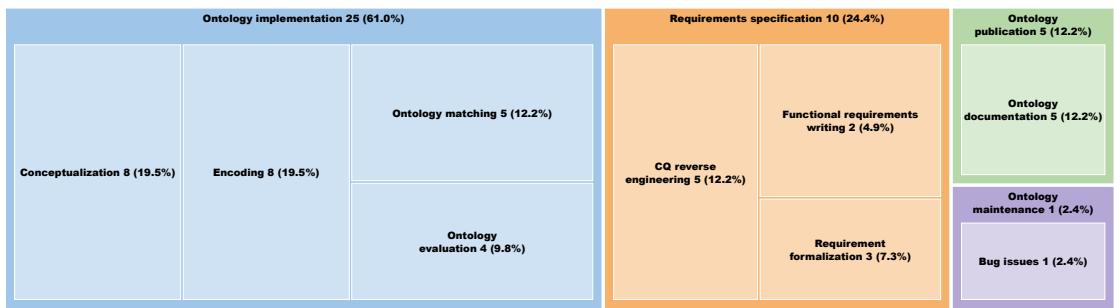


Figure 3. Distribution of LLM-supported tasks across ontology development phases based on 41 experiments from 30 papers. Numbers represent the total tasks identified for each phase, and percentages indicate their proportion relative to all tasks. Most tasks focus on ontology implementation (25 studies, 61.0%), followed by requirements specification (10 studies, 24.4%), publication (5 studies, 12.2%), and maintenance (1 study, 2.4%).

4.1.1 Ontology requirements specification

In the task of **functional requirements specification**, Fathallah et al. (2024a) proposed a method leveraging LLMs such as GPT-3.5, LLaMA, and PaLM to generate ontology requirements from natural language texts and CQs, within the framework of the NeOn-GPT methodology, using a wine ontology as a case study.

CQ reverse engineering has received growing attention by creating CQs directly from ontologies. Alharbi et al. (2024a) developed a pipeline that parses existing ontologies to extract relevant information, which is then used to instantiate prompts for the automated generation of candidate CQs. Rebboud et al. (2024a) introduced a benchmarking strategy that includes generating CQs from ontologies, using tools such as LangChain and Ollama.

³ <https://raw.githubusercontent.com/oeg-upm/llm4oe-slr/refs/heads/main/Figures/Taxonomic%20framework%20of%20LLM-supported%20ontology%20engineering%20tasks.svg>

Table 1. Summary of ontology development phases, tasks, resources, inputs, and outputs supported by LLMs. For studies applying LLMs at multiple workflow stages (e.g., [Doumanas et al. \(2024\)](#), [Kholmska et al. \(2024\)](#)), we list each task to separately to capture their distinct contributions.

Phase	Task	Resource	Inputs	Outputs
Requirements specification	Functional requirements writing	Fathallah et al. (2024a)	Natural language text	Natural language text
		Antia and Keet (2023)	Natural language text	CQs
	CQ reverse engineering	Rebboud et al. (2024a)	Ontologies	CQs
		Alharbi et al. (2024a)	Triples	CQs
		Ciroku et al. (2024a)	KGs	CQs
		Rebboud et al. (2024b)	Ontologies	CQs
	Requirement formalization	Alharbi et al. (2024b)	Triples	CQs
		Rebboud et al. (2024a)	Ontologies and CQs	Queries
		Tufek et al. (2024)	Natural language text or CQs	SPARQL Queries
Ontology implementation	Conceptualization	Kholmska et al. (2024)	Concepts	SPARQL Queries
		Rebboud et al. (2024a)	CQs	Ontologies
		Goyal et al. (2024)	Natural language text	Binary decision
		Coutinho (2024)	Natural language text	Summarization
		Kholmska et al. (2024)	Step 2:Natural language text Step 3:Natural language text	Step 2: Classes Step 3: Concepts
		Dong et al. (2024)	Natural language text, Ontologies	Natural language text
		Babaei Giglou et al. (2023)	Task A: Natural language text, lexical term Task B: Natural language text Task C: Natural language text	Task A: Term type Task B: Binary decision Task C: Binary decision
		Toro et al. (2024)	Term	JSON or YAML
		Pisu et al. (2024)	Nature language text	Relationships
	Encoding	Doumanas et al. (2024)	Phase 1: Natural language text Phase 2: Domain documents Phase 3: Natural language text and CQs	Phase 1: Ontologies Phase 2: Ontologies Phase 3: Ontologies
		Fathallah et al. (2024a)	Natural language text	CQs, Triples and Ontologies
		Caufield et al. (2024)	Natural language text	Ontologies
		Eells et al. (2024)	Natural language text	Natural language text and RDF
		Saeedizade and Blomqvist (2024)	CQs	Ontologies
		Mateiu and Groza (2023)	Natural language text	Axioms
		Tang et al. (2023)	Natural language text	Ontologies, JSON and Triples
	Ontology matching	da Silva et al. (2024)	Natural language text, Ontologies	Ontologies
		Zamazal (2024)	Natural language text and verbalized candidates	Binary decision
		Kholmska et al. (2024)	Step 4: Natural language text Step 6: Concepts, Ontologies, Natural language text	Step 4: Documentation Step 6: Mapping
		Hertling and Paulheim (2023)	Ontologies and Natural language text	Mapping
		He et al. (2023)	Natural language text	Binary decision
	Ontology evaluation	Norouzi et al. (2023)	Natural language text	Mapping
		Tsaneva et al. (2024)	Natural language text	Axioms
		Kholmska et al. (2024)	Step 5: Ontologies	Step 5: Natural language text
		Fathallah et al. (2024a)	Natural language text	Ontologies and Axioms
	Ontology publication	Zhang et al. (2025)	Ontologies and CQs	Binary decision
		Bischof et al. (2024)	Natural language text	Terms
		Rebboud et al. (2024a)	Ontologies	Documentation
		Kholmska et al. (2024)	Step 9: Ontology Extensions, Natural language text	Step 9: Documentation
		Fathallah et al. (2024a)	Natural language text, Ontologies	Documentation
Maintenance	Ontology documentation	Giri et al. (2024)	Terms	Documentation
		Kholmska et al. (2024)	Step 8: Natural language text	Step 8: Natural language text

Several additional contributions enrich this area. For example, [Ciroku et al. \(2024a\)](#) introduced RevOnt, a system for extracting CQs from knowledge graphs. [Rebboud et al. \(2024b\)](#) conducted a feasibility study comparing LLM-generated CQs with ground-truth examples. [Antia and Keet \(2023\)](#) presented AgOCQs, a pipeline that combines a text corpus with CQ templates with NLP techniques to generate CQs.

Once requirements and CQs are established, **requirement formalization** can automate transfer CQs into executable queries, a crucial step in ontology development. [Kholmska et al. \(2024\)](#) investigate the role of LLMs (e.g., ChatGPT, Bard, Perplexity AI) in OE with active learning, demonstrating their ability to generate SPARQL queries from CQs. Similarly, [Rebboud et al. \(2024a\)](#) benchmarked LLM-generated

ontology-aligned queries, evaluating them using structural metrics like Tree Edit Distance. Their results show that LLMs are able to capture ontology structure and user intent. Further supporting this, [Tufek et al. \(2024\)](#) successfully automated SPARQL query generation from natural language requirements, showing that LLMs can effectively connect human requirements with machine readable formalisms in OE.

4.1.2 Ontology implementation

The **conceptualization** task in the ontology implementation phase involves defining terms, relationships, and taxonomies. Our analysis identified 8 studies investigating the potential of LLMs in supporting these activities, highlighting it as one of the most prominent research areas in the field. One key aspect of ontology development is the generation of concept definitions. In addition, LLMs have also improved taxonomy discovery and relationship extraction. Studies such as [Goyal et al. \(2024\)](#) and [Babaei Giglou et al. \(2023\)](#) employed LLMs to support ontology formalization through automated reasoning and relation identification, showing that LLMs can detect both hierarchical and non-taxonomic relationships between concepts.

Several researchers have proposed integrated frameworks to support ontology conceptualization. For example, [Coutinho \(2024\)](#) developed a system merge text-based languages for ontologies with LLMs to generate new concepts based on contextual information for the unified foundational ontology (UFO) [Guizzardi et al. \(2015\)](#).

Further contributions include [Rebboud et al. \(2024a\)](#), who framed this task as constructing an ontology by generating missing classes and properties. [Kholmska et al. \(2024\)](#) applied LLMs to generate nearly 200 core concepts in the field of active learning, which were hierarchically organized and definitionally refined, demonstrating the potential of LLMs for concept discovery and structuring. [Dong et al. \(2024\)](#) explored concept generation, while [Toro et al. \(2024\)](#) introduced techniques to complete ontology terms. [Pisu et al. \(2024\)](#) investigated the use of language models for research topic taxonomy generating and construction.

Encoding refers to the translation of conceptual models into formal ontology representation languages. Our survey identified 8 studies that investigated how LLMs can support this process. In the context of domain-specific formalization, [Doumanas et al. \(2024\)](#) employed LLMs to develop an OWL ontology for search and rescue missions (SAR). Their evaluation was performed against the gold reference ontology in the SAR domain [Masa et al. \(2022\)](#).

Several studies propose tools for the translation of natural language into OWL. [Mateiu and Groza \(2023\)](#) created a Protégé plugin⁸ that converts natural language sentences into OWL axioms using LLMs. Similarly, [Caufield et al. \(2024\)](#) developed a pipeline that extracts procedural knowledge from websites (e.g., recipes) and have corresponding ontologies. Other works, including [Ells et al. \(2024\)](#) prompted LLMs to generate ontologies for common nouns and assessed the output in terms of syntactic validity and structural completeness. [Saeedizade and Blomqvist \(2024\)](#) investigated the use of LLMs to generate OWL from structured narratives, highlighting the potential of LLMs to transform textual descriptions into formal ontological representations. [Tang et al. \(2023\)](#) focused on domain-specific knowledge extraction, demonstrating how LLMs can facilitate the construction of ontologies tailored to specific road traffic domain for autonomous vehicles.

Next, [da Silva et al. \(2024\)](#) proposed a method to transform capability descriptions into ontological models using LLMs, reducing ontology creation from input of natural language. [Fathallah et al. \(2024a\)](#)

⁸<https://protege.stanford.edu/>

developed a pipeline that automates the ontology encoding task by instantiating structures with relevant data.

LLMs have also been applied to **ontology matching** tasks, which are key to ensure interoperability in diverse knowledge domains. [Zamazal \(2024\)](#) evaluated the effectiveness of LLMs in validating complex mapping candidates, indicating promising results in correspondence validation tasks. [Hertling and Paulheim \(2023\)](#) introduced OLaLa, a system that uses LLMs to generate high precision ontology mappings. Additionally, studies by [Norouzi et al. \(2023\)](#) and [He et al. \(2023\)](#) benchmarked the performance of LLMs in ontology alignment against reference mappings, revealing that modern LLMs can perform comparable to specialized alignment systems. [Kholmska et al. \(2024\)](#) further explored LLMs in generating initial mapping suggestions to support ontology extension, assessing concept coverage and inter-model consistency.

In the **ontology evaluation** task, LLMs have been applied to assess the quality, consistency, and correctness of ontologies. [Tsaneva et al. \(2024\)](#) utilized ChatGPT-4 to verify ontology restrictions, achieving high accuracy in detecting logical inconsistencies and structural problems. [Fathallah et al. \(2024a\)](#) explored a different approach, proposing an evaluation framework that leverages ChatGPT in ontology syntax correction, using parsing errors detected by RDFLib and pitfall descriptions from the OOPS! API [Poveda-Villalón et al. \(2014\)](#), particularly focusing on the missing disjointness axioms. This demonstrates that LLMs can not only identify ontology issues but also suggest corrective actions. Similarly, [Zhang et al. \(2025\)](#) introduced OntoChat, a framework for ontology verbalization and validation through prompt driven unit tests, aiming to make ontology evaluation more accessible. [Kholmska et al. \(2024\)](#) provided a broader evaluation of ontology quality, emphasizing relevance, content consistency, and structural soundness in LLM-supported ontology development.

4.1.3 *Ontology publication*

The generation of human-readable **documentation** is essential for understanding the definitions and relationships of an ontology. Our analysis identified 5 studies applying LLMs to ontology documentation tasks.

[Bischof et al. \(2024\)](#) employed LLMs to produce context-sensitive annotations aligned with domain-specific conventions. [Rebboud et al. \(2024a\)](#) explored the use of LLM to generate structured documentation of key ontology components, such as classes and properties; their evaluation, based on semantic similarity metrics, showed that the LLM-generated documentation is accurate and relevant. [Fathallah et al. \(2024a\)](#) further addressed natural language generation for ontology entities and properties, enhancing comprehensibility for both technical and non-technical users. In more specialized domains, [Giri et al. \(2024\)](#) applied the T5 language model to summarize functional descriptions of Gene Ontology terms, while [Kholmska et al. \(2024\)](#) leveraged LLMs to create comprehensive documentation for extended ontologies, supporting knowledge sharing and reuse.

4.1.4 *Ontology maintenance*

Among the studies reviewed, only one paper specifically addressed maintenance tasks related to **bug** or detection of **issues**. [Kholmska et al. \(2024\)](#) investigated the potential of LLMs to extract key improvement suggestions, refine task lists, and identify missing concepts from human-evaluated reports (step 8 of their proposed workflow). Their findings suggest that LLMs can effectively support ontology maintenance.

4.1.5 *Summary*

Based on the analysis of 41 studies from 30 papers, LLMs have been applied unevenly in different

ontology development phases. The implementation phase dominates, with 25 studies focused on conceptualization, encoding, matching, and evaluation. Requirements specification ranks second, represented by 10 studies addressing functional requirements, competency question generation, and formalization into SPARQL queries. Later stages receive limited attention: 5 studies focus on ontology publication through documentation generation, while only one addresses maintenance tasks.

4.2 RQ2: How do LLMs-based approaches support different ontology development activities?

Following the identification of ontology development tasks supported by LLMs in Section 4.1, we now explore the internal workings of how LLMs contribute to these tasks. This includes analyzing their functional roles (as ontology engineers or domain experts, etc.), model choices (from GPT series or other open-source tools), input and output types utilized by LLMs, and whether the studies collaborate with humans in the LLM-based activities. Table 1 displays the inputs and outputs associated with each ontology development activity. For a more detailed breakdown, including specific model names, functional roles, and human collaboration status, refer to Table 2 in the Appendix.

4.2.1 RQ2.a: What is the role of LLMs models in OE activities?

Based on the reviewed studies, LLMs take on several key collaborative roles within OE tasks, either complementing or, in some cases, replicating tasks traditionally performed by human knowledge engineers. These contributions can be grouped into four main categories:

1. **Ontology Engineer:** LLMs are increasingly functioning as automated Ontology Engineers, actively supporting the design, development, and maintenance of ontologies throughout the entire development lifecycle. More precisely, LLMs are utilized to (a) parse unstructured domain texts and generate structured requirement specifications, thereby facilitating automated requirement elicitation [Alharbi et al. \(2024a\)](#); [Ciroku et al. \(2024a\)](#); (b) transform competency questions into structured queries (e.g., SPARQL) [Rebboud et al. \(2024a\)](#); [Tufek et al. \(2024\)](#); (c) discover axioms, particularly identifying hierarchical relationships between concept pairs during the conceptualization activity [Goyal et al. \(2024\)](#); [Babaei Giglou et al. \(2023\)](#); (d) translate unstructured or semi-structured texts directly into OWL code [Doumanas et al. \(2024\)](#); [Eells et al. \(2024\)](#); [Saeedizade and Blomqvist \(2024\)](#); [Tang et al. \(2023\)](#); and (e) support the entire ontology lifecycle, from conceptualization through to documentation, or provide end-to-end assistance under methodologies such as the NeOn-GPT approach [Kholmska et al. \(2024\)](#); [Fathallah et al. \(2024a\)](#).
2. **Domain Experts:** LLMs act as domain experts by supporting knowledge extraction, term definition, and ontology content validation. They perform tasks requiring domain-specific understanding, such as (a) generating domain-relevant concepts [Dong et al. \(2024\)](#); (b) producing context-sensitive term annotations [Bischof et al. \(2024\)](#); (c) generating structured ontology documentation [Rebboud et al. \(2024a\)](#); [Giri et al. \(2024\)](#); and (d) summarizing functional descriptions [Consortium \(2006\)](#). They are also used in evaluation tasks requiring both technical and domain expertise to assess the consistency and correctness of ontology content [Tsaneva et al. \(2024\)](#); [Fathallah et al. \(2024a\)](#). (e) Additionally, LLMs assist in validating or suggesting domain-specific relations and constraints, ensuring alignment with established domain semantics [Babaei Giglou et al. \(2023\)](#); [Goyal et al. \(2024\)](#).

3. **Human Evaluator:** In some cases, LLMs have been placed as human evaluators, for example, to verify ontology axioms and assess their logical soundness [Tsaneva et al. \(2024\)](#).

4.2.2 RQ2.b: What types of LLMs are used in OE activities?

The LLMs employed in OE span a range of architectures and capacities. Based on our analysis, these models can be grouped into four major categories, each playing distinct roles in the OE lifecycle.

- **GPT series (GPT-3.5, GPT-4, GPT-4 Turbo/4o):** The GPT series is among the most widely used for tasks involving CQ reverse engineering, encoding, and evaluation, owing to their strong capabilities in natural language understanding and generation [Rebboud et al. \(2024b\)](#); [Tufek et al. \(2024\)](#); [Fathallah et al. \(2024a\)](#). In particular, GPT-4 Turbo/4o has been leveraged for more complex tasks requiring multi-formalism reasoning, such as verifying axioms across heterogeneous logical representations [Zamazal \(2024\)](#).
- **Open-Source large language models (LLaMA, Mistral, Claude, etc.):** Open source LLMs such as LLaMA [Touvron et al. \(2023a\)](#), Mistral⁹ and Claude¹⁰ are also used mainly in ontology development tasks, including functional requirement writing, conceptualization, encoding, etc. [Hertling and Paulheim \(2023\)](#) fine-tuned LLaMA for ontology matching and reuse, aligning anatomy ontologies in the OAEI benchmark. [Goyal et al. \(2024\)](#) leveraged LLaMA3 and Mistral to detect hierarchical relations in GeoNames and Schema.org. [Saeedizade and Blomqvist \(2024\)](#) combined LLaMA-generated outputs with expert feedback to iteratively refine a SAR ontology. [da Silva et al. \(2024\)](#) demonstrated that Claude 3 and Gemini Pro can effectively convert natural language descriptions into OWL axioms, supporting the ontology encoding process. Additionally, LLaMA and PaLM were integrated into the NeOn-GPTframework proposed by [Fathallah et al. \(2024a\)](#), supporting multiple stages of ontology development, including functional requirements, encoding, evaluation, and documentation.
- **Lightweight Instruction-Tuned Models (e.g., Mistral-7B, Falcon-7B-Instruct, etc.):** Lightweight instruction-tuned models have been applied in OE tasks, as demonstrated in two recent studies. [Alharbi et al. \(2024b\)](#) employed models such as LLaMA-2-70B, Mistral 7B [Jiang et al. \(2023\)](#), and Flan-T5-XL to generate CQs by embedding RDF triples into prompt templates enriched with varying levels of contextual information. The resulting CQs were then filtered to produce a final set of relevant, non-redundant questions. [Saeedizade and Blomqvist \(2024\)](#) further explored the use of lightweight open-source models including LLaMA-7B, LLaMA-13B, LLaMA-2-70B, Alpaca, Falcon-7B, and Falcon-7B-Instruct—for ontology encoding. Their study demonstrated the capability of these models to process narrative ontology descriptions and associated CQs for automated ontology creation, in comparison with models such as GPT-3.5, GPT-4, and Bard.
- **Transformer-Based Architectures (T5, BERT):** Beyond large-scale LLMs, pre-trained transformer models, such as T5 and BERT, are powerful in supporting sentence encoding, classification, and structured generation. [Ciroku et al. \(2024b\)](#) used T5 and SBERT within the RevOnt framework to

⁹<https://mistral.ai/>

¹⁰<https://www.anthropic.com/>

automatically extract competency questions from knowledge graphs. [Giri et al. \(2024\)](#) applied T5 in the GO2Sum system to generate human-readable functional descriptions of Gene ontology terms, supporting ontology documentation and publication. Furthermore, [Pisu et al. \(2024\)](#) proposed the use of SciBERT for the generation of taxonomy of research publication topics, with the objective of integrating domain-adapted language models into ontology encoding and KG construction workflows.

4.2.3 RQ2.c: What LLM prompt techniques are employed to support OE activities?

To understand how LLMs are operationalized within OE workflows, this subsection examines the prompting techniques used across the reviewed studies. The analysis covers the full range of strategies used to guide or adapt LLM behavior, including zero-shot and few-shot prompting, role-based prompting, template-based and representational prompting, reasoning-driven prompting, iterative refinement, retrieval-augmented prompting, and fine-tuning.

- **Zero-shot prompting:** Zero-shot prompting is the most frequently used strategy and is applied when tasks can be specified purely through natural-language instructions. It is used across requirements specification, conceptualization, encoding, and ontology matching. In many cases, zero-shot prompting is combined with structural templates to constrain output formats. Examples include CQ generation from textual descriptions or triples [Rebboud et al. \(2024b\)](#); [Alharbi et al. \(2024a\)](#), SPARQL query generation using instruction-only templates [Tufek et al. \(2024\)](#), and type classification using only local context [Goyal et al. \(2024\)](#). In ontology encoding, natural-language definitions are translated into OWL axioms via zero-shot templates specifying the expected syntax [Caufield et al. \(2024\)](#). Alignment approaches relying solely on verbalized labels also follow a pure zero-shot setup [He et al. \(2023\)](#); [Norouzi et al. \(2023\)](#). Zero-shot prompting is further used for capability modelling based on TBox grounding [da Silva et al. \(2024\)](#).
- **Few-shot and one-shot prompting:** Few-shot prompting augments instructions with a small number of examples, improving structural fidelity and reducing hallucinations. One-shot prompting provides a single demonstration when minimal scaffolding suffices. These techniques are widely used for CQ generation, conceptualization, evaluation, and matching. Few-shot examples improve CQ extraction [Rebboud et al. \(2024b\)](#), guide entity-relation extraction in NeOn-GPT [Fathallah et al. \(2024a\)](#), and support axiom evaluation and alignment [Tsaneva et al. \(2024\)](#); [Hertling and Paulheim \(2023\)](#). One-shot prompting is used to illustrate user-state structures [Zhang et al. \(2025\)](#) or capability modeling patterns [da Silva et al. \(2024\)](#). In several workflows, example-driven prompting interacts with decomposition strategies.
- **Template-based prompting:** Template-based prompting uses fixed syntactic or structural scaffolds such as JSON/YAML schemas, CQ templates, SPARQL skeletons, or OWL Functional Syntax, to constrain and standardize model outputs. This technique often appears in combination with zero-shot or few-shot prompting. Documentation templates specify fields like labels and definitions [Bischof et al. \(2024\)](#). Triple-based templates standardize CQ phrasing [Alharbi et al. \(2024a\)](#). Encoding pipelines frequently use JSON/YAML schemas specifying IRIs, definitions, and axioms [Toro et al. \(2024\)](#). SPARQL templates enforce good form and reduce ambiguity [Tufek et al. \(2024\)](#). Many workflows combine templates with iterative correction loops. [Tsaneva et al. \(2024\)](#) shows that providing axioms in the Rector or Turtle format improves the verification accuracy. Verbalized

labels, definitions, and structural fragments are also used in matching workflows [Hertling and Paulheim \(2023\)](#).

- **Role-based prompting:** Role-based prompting frames the model as an “ontology engineer”, “domain expert”, or “SPARQL specialist”, grounding instructions in domain expertise. This technique often appears in combination with zero-shot, few-shot, CoT, or template-based prompting. Role prompts are used in requirement specification [Alharbi et al. \(2024b\)](#), SPARQL generation [Kholmska et al. \(2024\)](#), conceptualization [Fathallah et al. \(2024a\)](#), documentation [Bischof et al. \(2024\)](#), ontology matching [Kholmska et al. \(2024\)](#), and evaluation [Fathallah et al. \(2024a\)](#).
- **Multi-step reasoning prompting (CoT, GoT, decomposition):** Reasoning-oriented prompting guides models through intermediate steps or decomposed subtasks. Chain-of-thought prompting supports term extraction, classification, and axiom justification [Fathallah et al. \(2024a\)](#). Graph-of-Thoughts prompting enables multi-branch exploration of ontology structures [Saeedizade and Blomqvist \(2024\)](#). Decomposition strategies, often combined with templates or examples, break workflows into sequential steps (e.g., concepts → definitions → properties → axioms) as in ontology encoding [Tang et al. \(2023\)](#). Multi-step reasoning is also used in the validation of axioms [Tsaneva et al. \(2024\)](#).
- **Iterative and conversational refinement prompting:** Many OE workflows employ multi-turn refinement, where the model progressively revises outputs based on constraints or feedback. This includes SAR ontology construction [Kholmska et al. \(2024\)](#), multi-phase encoding pipelines [Doumanas et al. \(2024\)](#), and multi-turn axiom correction [Fathallah et al. \(2024a\)](#). RevOnt [Ciroku et al. \(2024a\)](#) implements staged refinement for verbalization abstraction, generalization, and CQ filtering. Conversational refinement systems enable users to interactively adjust generated CQs or alignments [Zhang et al. \(2025\)](#).
- **Fine-tuning and model adaptation:** A small subset of studies use supervised fine-tuning to adapt models to OE tasks. GPT-3 has been adapted for NL-to-OWL translation tasks through task-specific prompting or tuning [Mateiu and Groza \(2023\)](#). T5 is fine-tuned on GO annotations for documentation [Giri et al. \(2024\)](#). The placement of Domain-specific concepts is enhanced through a fine-tuned BERT cross-encoder [Dong et al. \(2024\)](#). SciBERT is fine-tuned for the extraction of scientific relationships [Pisu et al. \(2024\)](#). In [Rebboud et al. \(2024b\)](#), most models are used in fine-tuned configurations, including FusionNet_7Bx2_MoE_14B SOLAR-10.7B-Instruct-v1.0, Mistral-7B and another Mistral-7B-v0.1. Although rare in general, fine-tuning yields notable gains for tasks requiring high structural or domain precision.

4.2.4 RQ2.d: What are the inputs given to LLMs? and What are the outputs from the LLMs?

To better analyze the use of LLMs during the OE lifecycle, we contextualize the input given to the LLMs in relation to the expected output and the specific task at hand. For this reason, in this section we report the results obtained for RQ2.c and RQ2.d and group the results according to RQ1 which acts as the backbone for this survey and a natural way of grouping, as the OE activities are driven by the type of their expected output.

- During the **ontology requirement specification** phase there are common patterns depending on the activity at hand. More precisely: (a) taking as input natural language text to write functional

requirements either in the shape of CQs (Antia and Keet (2023)) or natural language affirmative statements (Fathallah et al. (2024a)); (b) transforming structured inputs (ontologies, triples or KGs) to write CQs through reverse engineering (Rebboud et al. (2024a); Alharbi et al. (2024a); Ciroku et al. (2024b); Rebboud et al. (2024b); Alharbi et al. (2024b)); and (c) taking ontologies and natural language (including CQs) to generate queries as part of the requirement formalization activity.

- For the **ontology implementation** phase, there are common patterns for activities with clear output formats such as ontology encoding and ontology matching. However, approaches addressing less restricted activities, such as ontology conceptualization or evaluation, present higher variability. More precisely:
 - While all approaches take natural language text as input in different formats, as is typically the case for OE projects, the **ontology conceptualization** activity leads to various types of outputs. Some approaches generate machine-readable representations, such as ontologies in OWL (Rebboud et al. (2024a)) or structured schemas in JSON or YAML Toro et al. (2024). Others produce concepts or terms intended for ontology integration Kholmska et al. (2024); Babaei Giglou et al. (2023). Also, some approaches generate natural language descriptions (Dong et al. (2024)), or binary decisions to validate semantic relations or classify term types (Goyal et al. (2024); Babaei Giglou et al. (2023)). A special classification task is presented by Pisu et al. (2024), to predict semantic relations (e.g., supertopic, subtopic, same-as, other) between topic pairs extracted from an existing ontology.
 - For the **ontology encoding** activity, most analyzed approaches (Doumanas et al. (2024); Fathallah et al. (2024a); Caufield et al. (2024); Eells et al. (2024); Mateiu and Groza (2023); Tang et al. (2023); da Silva et al. (2024)) take natural language descriptions as input to generate ontology artifacts in OWL, RDF, or related formats. An exception is Saeedizade and Blomqvist (2024), which uses competency CQs as input to guide ontology generation in alignment with user information needs. Regarding outputs, most approaches produce complete ontology code, with exceptions like Mateiu and Groza (2023) which focuses specifically on generating OWL axioms. In Eells et al. (2024), the LLM is prompted with a single noun (e.g., "air," "book") and returns a mix of natural language text and RDF ontology content.
 - To address **ontology matching**, some of the analyzed works take natural language inputs to produce binary decisions indicating semantic alignment. For example, Zamazal (2024) uses LLMs to classify verbalized complex correspondence candidates as (probably) positive or negative, while He et al. (2023) evaluates the equivalence of concept pairs based on their names and hierarchical contexts, outputting a "Yes" or "No" response. Other approaches directly generate ontology mappings. Norouzi et al. (2023) takes structured representations of two ontologies (in the form of subject–predicate–object triples), and outputs a set of proposed alignments between classes or properties. Kholmska et al. (2024) approaches ontology reuse through a multi-step process: Step 4 employs LLMs to extract key features—such as purpose, reused elements, and formats from existing ontologies to support reuse decisions; Step 6 involves using LLMs to map new concepts to the previously identified ontologies by analyzing their definitions, relationships, and properties. The output consists of explicit mappings expressed as `owl:sameAs`, `owl:equivalentClass`,

and `owl:equivalentProperty` statements. Similarly, [Hertling and Paulheim \(2023\)](#) combines textual and structural information to generate formal ontology alignments.

- For **ontology evaluation** some approaches take natural language text as input ([Tsaneva et al. \(2024\)](#); [Fathallah et al. \(2024a\)](#)), which may include evaluation reports ([Fathallah et al. \(2024a\)](#); [Kholmska et al. \(2024\)](#)), while others also utilize structured ontology-related information or ontologies ([Kholmska et al. \(2024\)](#); [Zhang et al. \(2025\)](#)). The ontology evaluation activity results in various types of output. Some approaches generate machine-readable corrections or modifications, such as class value replacements or the addition of disjointness axioms [Fathallah et al. \(2024a\)](#). Others produce natural language assessments regarding ontology relevance, structural completeness, and alignment with standard frameworks such as CRISP-DM [Kholmska et al. \(2024\)](#). Another line of work focuses on classifying and verifying individual axioms as correct or defective, optionally specifying the type of modeling defect [Tsaneva et al. \(2024\)](#). Alternatively, one study outputs binary decisions such as Yes/No judgments to validate the coverage of CQs based on the ontology content [Zhang et al. \(2025\)](#)
- To address **ontology documentation** activity, all analyzed approaches focus on generating human-readable documentation. They take ontologies or terms as input ([Rebboud et al. \(2024a\)](#); [Giri et al. \(2024\)](#)), and optionally incorporate additional natural language text sources ([Kholmska et al. \(2024\)](#); [Fathallah et al. \(2024a\)](#)). Specifically, [Rebboud et al. \(2024a\)](#) emphasizes the production of readable summaries highlighting key classes and properties. [Giri et al. \(2024\)](#) generates concise summaries from Gene Ontology terms. Finally, [Kholmska et al. \(2024\)](#) leverages LLMs to assist in the writing of technical reports.
- The only work explicitly addressing **ontology maintenance** is [Kholmska et al. \(2024\)](#), where LLMs are used to support iterative refinement. In Step 8 of their workflow, domain expert feedback and validation reports serve as input. These documents are uploaded to an LLM interface, where the model reviews the content, extracts improvement suggestions, and generates refined task lists. The output is human-readable text highlighting missing concepts, potential relationship issues, and areas requiring adjustment within the ontology. While the ontology itself is not used as direct input, its structure is implicitly referenced through the content of the validation reports.

4.2.5 RQ2.e: What is the role of humans in OE LLM-assisted activities?

Although many recent studies automate ontology development with LLMs, only 4 studies explicitly involve human participants, typically domain experts or ontology engineers, to support tasks requiring judgment, contextual understanding, and refinement.

[Doumanas et al. \(2024\)](#) highlight the crucial role of domain experts during the ontology encoding phase. The experts were responsible for evaluating both existing ontologies and LLM-generated semantic content, ultimately steering the model toward the creation of a new ontology tailored for SAR operations. Similarly, [Kholmska et al. \(2024\)](#) describe the involvement of domain experts and end-users during ontology maintenance and bug resolution. Their iterative feedback on errors and inconsistencies was critical to refine the ontology structure and enhance overall quality. In the context of ontology evaluation, [Zhang et al. \(2025\)](#) demonstrate how ontology engineers curated user stories that were manually authored or derived from earlier development stages to support meaningful CQ extraction, emphasizing the need for human input to link technical outputs to real-world use cases. Finally, [Alharbi et al. \(2024a\)](#) report

interviewing human experts and ontology engineers to capture design intentions. These insights were then used to generate contextually accurate CQs, particularly in support of functional specification and requirements engineering.

4.2.6 Summary

Across the 30 reviewed studies, LLMs assume three functional roles in ontology engineering: **Ontology Engineer**, **Domain Expert**, and **Human Evaluator**. Most studies rely on general-purpose models such as GPT-3.5 and GPT-4, with growing adoption of open-source models including LLaMA, Mistral, and Falcon. Current workflows predominantly use LLMs to automate the generation, transformation, and verification of ontology artefacts, with human involvement remaining limited. Building on these model choices, the studies apply a wide range of prompting strategies. **Zero-shot** and **few-shot** prompting are the most common, while **template-based** prompts are adopted when outputs must follow predefined schemas. **Role-based prompting** contextualizes instructions, and **multi-step reasoning** (CoT, GoT, decomposition) together with **iterative refinement** supports staged modelling and corrective workflows. Fine-tuning is used only in a minority of studies that require domain adaptation or high syntactic precision. Across these prompting settings, inputs range from unstructured text and competency questions to structured triples, knowledge graph fragments, and ontology modules. Outputs include classes, properties, OWL axioms, SPARQL queries, competency questions, natural-language definitions, and documentation. Only a small subset of studies involve explicit human feedback, typically through expert validation or interactive refinement.

4.3 RQ3: How is the performance of LLMs in ontology development evaluated?

In this section, we analyze the experimental support provided in the reviewed studies to validate their proposed frameworks and methodologies. Specifically, we examine whether these studies include experiments and whether they are open-source, as transparency is essential for reproducibility and independent validation. We also investigate the datasets used in these studies to determine if a common benchmark was used across different studies. Most importantly, we assess the performance of LLMs in ontology development, focusing on the evaluation methods (quantitative, qualitative, or hybrid) and the specific metrics used, such as F1, BLEU, or others. These details allow us to thoroughly assess the reported performance results from these papers and evaluate the effectiveness of LLMs in addressing various ontology engineering challenges. Table 3 in Appendix 7 compiles and summarizes all information on the availability of experiments, datasets used, evaluation types, and evaluation metrics applied across reviewed studies.

4.3.1 RQ3.a Does an experiment exist?

Out of the 41 reviewed studies, 14 report no experimental evaluation. The remaining 27 include experiments, among which 4 studies exclusively perform isolated LLM tests without baselines or comparative analysis, all of which originate from the same paper Fathallah et al. (2024a), appearing across multiple OE tasks. Another 4 studies report experiment results but do not provide public access link Tsaneva et al. (2024); Alharbi et al. (2024b); Norouzi et al. (2023); Fathallah et al. (2024a). The remaining 19 studies include experiments with evaluation metrics and comparative analysis in their accessible resources. Note that, not only Fathallah et al. (2024a) but also Kholmska et al. (2024) address multiple tasks, ranging from requirements specification to addressing bug issues. Therefore, these approaches appear multiple times in our analysis.

4.3.2 RQ3.b What data sets are used in the evaluations?

Although not all studies include full experiments, many of them still explicitly mention the datasets used in their work. An exception is the study by Bischof et al. [Bischof et al. \(2024\)](#), which does not specify any dataset names. Instead, it refers to terms or concepts without providing detailed information about the data sources involved. Through the other 40 studies, all explicitly describe their dataset types and provide publicly accessible datasets through platforms such as GitHub, Zenodo, or some official ontology database (e.g., GO, OntoDM Ontology). From these 40 studies, 38 use ontology related files (OWL, RDF, etc.) as their primary dataset type.

Drilling into the detailed datasets used, Alharbi et al. [Alharbi et al. \(2024b\)](#) selected four ontologies along with their associated CQ datasets to investigate CQ creation. Three of these ontologies: Video Game (entertainment) [Parkkila et al. \(2017\)](#), Dem@care (healthcare) [Karakostas et al. \(2016\)](#), and VICINITY Core (Internet of Things) [Cimmino et al. \(2019\)](#) were obtained from the CORAL [Fernández-Izquierdo et al. \(2019\)](#) repository, a comprehensive source for CQs. The fourth ontology, African Wildlife (ecology) [Keet \(2019\)](#), was included to ensure diversity in both domain coverage and CQ styles.

Meanwhile, [Dong et al. \(2024\)](#) applied the MM-S14-Disease and MM-S14-CPP datasets [Dong et al. \(2023\)](#), both from the biomedical domain, to evaluate LLM performance in ontology mapping. After encoding the ontologies into OWL using syntax-aware concepts derived from textual descriptions, they leveraged version differences in SNOMED CT [Donnelly et al. \(2006\)](#), a clinical terminology system, to define new concepts and construct ground-truth placement edges. Similarly, [Kholmska et al. \(2024\)](#) used the OntoDM suite [Panov et al. \(2008\)](#) and IOF Core [Drobnjakovic et al. \(2022\)](#), both rooted in the industrial engineering domain, due to their maturity, comprehensive documentation, and validation within real-world manufacturing settings.

[Ciroku et al. \(2024a\)](#) introduced the first implementation of RevOnt, which leverages the Web Data Visualizer Knowledge Graph (WDV) [Amaral et al. \(2022\)](#) constructed from Wikidata [Vrandečić and Krötzsch \(2014\)](#), a collaborative knowledge base. WDV comprises 7.6K unique RDF triples and includes manually annotated competency questions, providing explicit subject–predicate–object relationships that serve as ground truth for CQ derivation. This resource enables the quantitative evaluation of data verbalization models (e.g., via BLEU score), comparing LLM-generated questions to human-authored ones. [Tsaneva et al. \(2024\)](#) used food domain Pizza Ontology in Protégé to benchmark LLM-driven defect detection in OWL axioms. [Giri et al. \(2024\)](#) focused on the summarization of protein functions in the bioinformatics domain, evaluating the generated outputs against GO [Consortium \(2006\)](#), a fundamental resource in molecular biology. Similarly, [Toro et al. \(2024\)](#) evaluated the quality of LLM-generated definition generation for biomedical Cell ontology [Diehl et al. \(2016\)](#) using BERTScore, supplemented with manual expert review to ensure semantic validity.

We also observed that several studies share common experimental ontologies, enabling standardized evaluation and comparative analysis. For ontology matching tasks, studies such as [Zamazal \(2024\)](#), [Hertling and Paulheim \(2023\)](#), and [Norouzi et al. \(2023\)](#) utilized datasets from the OAEI 2022 benchmark tracks, which provide both ontologies and KGs across diverse domains. Similarly, [Babaei Giglou et al. \(2023\)](#) and [Goyal et al. \(2024\)](#) adopted benchmark ontologies from the LLMs4OL Challenge, designed to assess LLM in various ontology learning tasks. This challenge spans multiple domains, including WordNet (lexical) [Miller \(1995\)](#), GeoNames (geospatial) [Volz et al. \(2007\)](#), UMLS [Bodenreider \(2004\)](#)

and SNOMED CT (biomedical) [Donnelly et al. \(2006\)](#), and Schema.org (web) [Guha et al. \(2016\)](#)¹¹ ontologies. These shared benchmarks facilitate consistent evaluation of LLM-based methods in structured knowledge engineering.

Furthermore, several datasets have been reused in studies to enable consistent evaluation in tasks and models. For example, [Fathallah et al. \(2024a\)](#) used the Wine Ontology as a gold standard in their NeOn-GPT pipeline, covering tasks such as requirements writing, OWL encoding, publication, and documentation. [Rebboud et al. \(2024a\)](#) and [Rebboud et al. \(2024b\)](#) evaluated LLM-generated outputs using a consistent set of ontologies: DOREMUS [Achichi et al. \(2018\)](#), Polifonia [de Berardinis et al. \(2023\)](#), Dem@Care [Karakostas et al. \(2016\)](#), Odeuropa [Lisena et al. \(2022\)](#), NORIA-O [Tailhardat et al. \(2024\)](#) and FIBO [Bennett \(2013\)](#) in multiple tasks, including CQ reverse engineering, conceptualization, and ontology documentation.

In addition to ontology files, several studies have explored the use of unstructured datasets and natural language texts as experimental input. [Mateiu and Groza \(2023\)](#) used 150 unstructured descriptions of ontological elements to evaluate a Protégé plugin that translates natural language sentences into OWL axioms. In a different setting, [Antia and Keet \(2023\)](#) used COVID-19 scientific papers as input to an automated CQ reverse engineering pipeline, in order to extract meaningful queries for ontology validation. [Eells et al. \(2024\)](#) focused on the construction of the ontology, using 101 high-frequency nouns from the Corpus of Contemporary American English (COCA) [Davies \(2010\)](#) as prompts. These nouns that cover general concepts were used to guide LLMs in generating ontological structures, which were then evaluated for semantic coherence and alignment with human common sense knowledge. To support further exploration of datasets used in LLM-based ontology engineering tasks, we provide Table 5 in the Appendix. The table lists acronyms and the full name of the datasets, the official or commonly used access link, and its associated domain, helping readers identify suitable datasets for specific domain applications.

4.3.3 RQ3.c: What evaluation methods are used?

Next, we examine how performance is evaluated, i.e., whether it is based on comparison against a reference standard or by applying specific scoring metrics. We also examine the type of evaluation methods used, distinguishing between quantitative approaches and qualitative approaches. In addition, we explore the evaluation metrics applied in these studies, such as F1, BLEU score, or human evaluation criteria. Finally, we assess whether human involvement is included in the evaluation process, through expert reviews or manual selection.

Of the 41 reviewed studies, we found that 9 do not conduct any explicit evaluation. These studies span different OE tasks and include the works reported in [Fathallah et al. \(2024a\)](#); [Tang et al. \(2023\)](#); [Mateiu and Groza \(2023\)](#); [Kholmska et al. \(2024\)](#); [Bischof et al. \(2024\)](#). Specifically, several studies completely lack experiment implementation and therefore do not provide any form of empirical evaluation [Tang et al. \(2023\)](#); [Mateiu and Groza \(2023\)](#); [Kholmska et al. \(2024\)](#); [Bischof et al. \(2024\)](#). Moreover, the work in [Fathallah et al. \(2024a\)](#) adopts a multi-step pipeline but only presents illustrative demonstrations, without comparative baselines or metric-based analysis.

Here, we focus on studies that include an explicit evaluation. The remaining work assesses the development of LLM-driven ontologies based on three main evaluation approaches, which are described below.

¹¹<https://schema.org>

- **Quantitative Evaluation Approach**

Most studies adopt quantitative methods, using automated metrics to assess LLM performance:

- **Performance-based evaluation:** Metrics such as precision, recall, and F1-score are widely used, alongside specialized metrics like inter-model consistency or error rate reduction, particularly in tasks like ontology matching and conceptualization. For example, [Hertling and Paulheim \(2023\)](#) evaluated ontology matching results using precision, recall, and the F1 score, compared to the OAEI datasets. Similarly, [Goyal et al. \(2024\)](#) and [Babaei Giglou et al. \(2023\)](#) apply the F1 score to measure the accuracy of LLM-generated outputs in ontology conceptualization tasks, as part of the LLMs4OL challenge. [Alharbi et al. \(2024b\)](#) and [Kholmska et al. \(2024\)](#) report task-specific metrics such as intermodel consistency, error rate reduction, and concept coverage to assess the quality of generated ontologies. [Dong et al. \(2024\)](#) evaluate hierarchical relation predictions using the Insertion Rate at top k (InR@k), which reflects how accurately new concepts are inserted into a taxonomy. [Tufek et al. \(2024\)](#) measure the accuracy of the exact match for the generation of SPARQL queries by comparing the outputs with predefined targets.
- **Similarity-based evaluation:** Some studies apply semantic similarity measures, such as SentenceBERT cosine similarity, to compare LLM-generated outputs against reference texts, reducing the need for manual comparisons. [Rebboud et al. \(2024b\)](#) use SentenceBERT cosine similarity to evaluate the semantic relationship between LLM-generated competency questions and expert references. In a related setting, [Rebboud et al. \(2024a\)](#) propose cosine similarity to compare generated ontology documentation with expert definitions, supporting an efficient and consistent quality assessment.
- **Ground-truth-based evaluation:** Structural fidelity is evaluated through metrics like tree edit distance (for SPARQL queries) [Rebboud et al. \(2024a\)](#) or BLEU score (for generated CQs) [Ciroku et al. \(2024a\)](#), ensuring alignment with gold standard datasets. While BLEU focuses on surface level lexical similarity, it remains a valuable metric of textual fidelity in structured natural language generation tasks, particularly in the context of CQ reverse engineering .

- **Qualitative Evaluation Approach**

A smaller number of studies employ only human based evaluation. Domain experts assess LLM outputs based on semantic precision, conceptual correctness, and domain relevance, providing critical insights beyond automated metrics. [Zhang et al. \(2025\)](#) utilizes a qualitative assessment approach through expert-driven questionnaires, where ontology engineers and domain experts provide nuanced feedback. [Bischof et al. \(2024\)](#) incorporates a rigorous qualitative evaluation that relies on experts in their work, in which specialized experts meticulously assess the definitions generated by LLMs for semantic precision, conceptual precision, and domain-specific correctness.

- **Hybrid Evaluation Approach**

Several studies integrate both quantitative and qualitative evaluations. They combine metric-based assessments with expert reviews to validate both the structural quality and practical usability of the LLM outputs, enhancing evaluation robustness. [da Silva et al. \(2024\)](#) combine SHACL-based syntax checks with expert review to ensure logical consistency and eliminate redundancy

in generated ontologies. [Giri et al. \(2024\)](#) integrate human evaluation to validate the embedding-based confidence scores used for assessing LLM-generated biomedical summaries. The study examines the correlation between automated and expert ratings, particularly when high embedding scores are observed. [Coutinho \(2024\)](#) adopt a hybrid evaluation approach, combining quantitative measures (e.g., task completion time, model quality metrics) with qualitative insights from expert interviews and user satisfaction assessments. This strategy improves inter-model consistency and enhances overall usability by balancing automation with human feedback. [Alharbi et al. \(2024a\)](#) also implement both quantitative and qualitative evaluation. On the quantitative side, they compare the number and distribution of generated CQs against existing ones, using metrics such as mean questions per triple, precision, recall, and F1-score. Qualitatively, they conduct expert interviews with ontology developers to assess the intent and relevance of generated CQs, further involving ontology editors to rate predicted versus curated definitions. Finally, [Tsaneva et al. \(2024\)](#) examine the use of ChatGPT-4 for verifying ontology restrictions. The study compares the performance of LLM-driven evaluations against human expert assessments to determine the feasibility and reliability of automated verification.

4.3.4 RQ3.d: What are the performance results from the evaluation?

As reported in previous sections, the reviewed works use different input datasets and metrics, and hence are not directly comparable. However, here we discuss the overall reported results, grouped by activity, to obtain a qualitative overview of the state of the art.

Among the requirements specification phase, LLMs are reported to be effective in producing CQs aligned with original ontology design intentions, achieving high recall across various benchmarks [Rebboud et al. \(2024b\)](#); [Antia and Keet \(2023\)](#); [Alharbi et al. \(2024a\)](#). Proprietary models consistently outperformed open-source ones, while the latter showed greater variance in performance (recall ranging from 0.58 to 1.00), largely due to differences in training data and architecture [Rebboud et al. \(2024a\)](#). Lower temperature settings were found to reduce hallucinations without compromising accuracy [Rebboud et al. \(2024a\)](#).

Notably, the RevOnt framework [Ciroku et al. \(2024a\)](#) achieved strong performance, with a median BLEU score of 0.41 in verbalization and 0.30 in question generation. Over 75% of its outputs were rated as good to high quality, particularly excelling in object-centric questions. [Rebboud et al. \(2024b\)](#) focused on automated CQ reverse engineering as the primary task. Specifically, *Zephyr* β and *UNA* achieved high precision when evaluated on their ability to generate relevant CQs for RDF-based ontologies such as DOREMUS and Odeuropa. Furthermore, the *AgOCQs* framework [Antia and Keet \(2023\)](#) demonstrated strong performance in generating CQs aligned with ontology design expectations. In a manual evaluation by domain experts, over 80% of the LLM-generated CQs were rated as both grammatically correct and semantically relevant, indicating the effectiveness in model to produce high quality queries.

In a complementary line of work, the RETROFIT-CQ pipeline [Alharbi et al. \(2024a\)](#) focused on adapting CQs to existing ontologies by generating questions from RDF triples. The evaluation showed that more than 75% of the generated CQs were directly executable as SPARQL queries without requiring manual revision, demonstrating the development of high structural ontology compatibility. In the requirement formalization task, LLMs demonstrated strong performance in translating natural language into SPARQL queries. [Tufek et al. \(2024\)](#) reported F1 scores ranging from 88% to 96%, with prompt template optimization significantly enhancing output quality. The execution modality also mattered: the use of a web interface yielded 100% F1, outperforming API-based execution 93%.

In the ontology implementation phase, particularly in conceptualization, GPT-4o demonstrated strong zero-shot performance in the LLMs4OL challenge tasks, achieving an F1 of 72.78% and winning six subtasks [Goyal et al. \(2024\)](#); [Babaei Giglou et al. \(2023\)](#). Fine-tuning of the Flan-T5 models led to substantial improvements, 25% in Task A and 45% on WordNet-related tasks. In domain-specific ontology construction, SciBERT achieved 91.29% F1 and over 91% accuracy by supporting term typing and taxonomy discovery [Pisu et al. \(2024\)](#). For hierarchical concept placement, models enhanced with explainability-driven instruction tuning, such as LLaMA-2-7B, outperformed larger general-purpose LLMs [Dong et al. \(2024\)](#).

During encoding and implementation, prompt engineering and iteration were reported to produce mixed results. In the SPIRES framework, GPT-3.5-turbo enabled perfect entity alignment, but for zero-shot chemical-disease relation tasks, SPIRES achieved 43.8 F1 [Caufield et al. \(2024\)](#). Claude and similar fine-tuned models showed superior performance in constraint generation, outperforming the baseline GPT in capability ontology generation [da Silva et al. \(2024\)](#). In SAR use cases, GPT-4 with Chain-of-Thought prompting produced *reusable* OWL ontologies [Doumanas et al. \(2024\)](#), i.e., ontologies that exhibit semantic consistency, modular design, and generalizability across multiple domains.

In ontology matching and reuse, GPT-4o correctly validated complex alignments with 100% accuracy in rejecting false correspondences [Zamazal \(2024\)](#). The OLaLa study showed F1 score improvements with LLaMA 2 (70B), optimized for efficiency [Hertling and Paulheim \(2023\)](#). Flan-T5-XXL also performed best overall in alignment tasks across benchmarks [He et al. \(2023\)](#), while conversational prompting approaches reported balanced recall and precision, benefiting from expert feedback [Norouzi et al. \(2023\)](#).

In ontology evaluation, ChatGPT-4 verified axioms with 92.2% accuracy, improving to 96.7% via ensemble aggregation [Tsaneva et al. \(2024\)](#). OntoChat received 87.5% positive ratings from experts for clustering competency questions [Zhang et al. \(2025\)](#). DRAGON-AI demonstrated high precision but moderate recall, iteratively improving with user input [Toro et al. \(2024\)](#). In a controlled educational setting, LLMs using CQ-by-CQ prompting approximated student-level ontology quality [Saeedizade and Blomqvist \(2024\)](#).

Finally, in the bug issue task, GO2Sum [Giri et al. \(2024\)](#) shown strong performance in summarizing Gene ontology annotations. It produced readable and semantically coherent descriptions even for low-confidence predictions. These scores reflect the percentage of summaries judged as helpful for understanding low-scoring Gene ontology predictions, indicating the effectiveness of LLMs in supporting ontology debugging and interpretation.

4.3.5 Summary

Evaluation practices in LLM-based ontology engineering mainly adopt quantitative metrics such as precision, recall, F1-score, and semantic similarity. Several studies combine these with qualitative expert reviews to assess conceptual validity and domain relevance. Most evaluations focus on overall system output rather than isolating LLM performance, often using existing ontologies (e.g., SNOMED CT, FIBO) as benchmarks. Open-source datasets are increasingly used to improve reproducibility, while standardized protocols remain scarce. Several emerging initiatives, such as OAEI and LLMs4OL, have begun to define shared datasets and metrics. In general, evaluation remains fragmented in all studies, lacking unified criteria and alignment of the standards.

4.4 RQ4: What are the main application domains where LLMs have been applied in the development of ontology?

In this section, we examine the domain-specific applications of LLMs in OE. *Healthcare and life sciences* represent one of the most extensively explored areas. LLMs have been applied to validate ontological constraints in major biomedical terminologies such as SNOMED CT and UMLS Tsaneva et al. (2024), and to assist in developing domain-specific ontologies like DemCare for dementia care Rebboud et al. (2024a,b). Furthermore, they support biomedical knowledge enrichment tasks in widely adopted resources such as the GO, MONDO, and the Cell Ontology, either by generating functional summaries Giri et al. (2024) or extending axioms and class definitions Caufield et al. (2024); Toro et al. (2024). *Cultural heritage industries* also benefit from LLMs. Ontologies such as DOREMUS, Polifonia, and Odeuropa are enhanced for music and olfactory heritage representation Rebboud et al. (2024a,b); Zhang et al. (2025). In the *finance* domain, LLMs are used for automated CQ reverse engineering and benchmarking of ontologies such as the Financial Industry Business Ontology (FIBO) Rebboud et al. (2024a,b), thus contributing to a more systematic knowledge organization in regulatory and investment contexts. Within *emergency and safety* domain, LLMs have been utilized to construct SAR ontologies based on related knowledge, including environmental conditions, hazard classification, and resource planning through structured prompting strategies Doumanas et al. (2024). In the autonomous systems and smart technologies domain, LLMs have been used to model traffic scenarios in autonomous driving ontologies Tang et al. (2023) and to define concepts for smart building systems Bischof et al. (2024), allowing automation and validation processes. For *academic and research domains*, LLMs help structure and classify research topics, as seen in the Computer Science Ontology (CSO) Pisu et al. (2024), offering scalable solutions for scientific knowledge organization and retrieval. In the *food* field LLMs support the enrichment of ontologies like FoodOn by extracting structured data from recipe texts Caufield et al. (2024), aiding in the classification of ingredients, preparation methods, and nutritional profiles.

4.4.1 Summary

Overall, these applications highlight the versatility of LLMs across diverse ontology-driven domains (see Table 4 in the Appendix for more details). Most research focuses on life sciences and healthcare, followed by cultural heritage, finance, emergency management, autonomous systems, and academic knowledge organization. Typical applications include ontology enrichment, documentation, CQs generation, and schema extension. Biomedical ontologies such as SNOMED CT, UMLS, and Gene Ontology dominate dataset usage, while cultural and financial ontologies (e.g., DOREMUS, FIBO) are also recurrent.

5 Discussion

Below, we explore the implications of our findings in relation to our RQs, highlighting the challenges and opportunities they present.

5.1 Supporting ontology development activities with LLMs

Among the studies reviewed, LLMs have been integrated into various stages of the ontology development lifecycle, with research concentrated predominantly in the early and middle phases. Activities related to ontology implementation, particularly conceptualization and encoding, have received the greatest attention, together representing about 88% of the reviewed works, while later stages such as evaluation

and maintenance remain comparatively underexplored. In these core phases, LLMs demonstrate notable advantages: by leveraging their strong natural language understanding and generative reasoning capabilities, they can automatically extract domain specific concepts, infer hierarchical relations, and identify semantic patterns from unstructured text. Empirical evidence indicates that the resulting concept taxonomies often approximate expert-curated ontologies in terms of scalability and semantic coherence [Caufield et al. \(2024\)](#); [da Silva et al. \(2024\)](#); [Doumanas et al. \(2024\)](#), accelerating the creation of structured and high quality knowledge representations in ontology development.

Despite notable advances, the application of LLMs across the ontology lifecycle remains uneven. Later-stage activities such as documentation, evaluation, and maintenance, receive limited attention, as they demand capabilities that current LLMs cannot reliably provide. Evaluation requires strict logical consistency verification, which exceeds the intrinsic reasoning capacity of LLMs without external validation mechanisms such as rule checkers or expert review [Toro et al. \(2024\)](#); [Liu et al. \(2025b\)](#). Maintenance, in turn, depends on dynamic knowledge integration, whereas LLMs are statically trained and cannot incorporate new information without retraining, which limits their suitability for the long-term evolution of the ontology [Mundlamuri et al. \(2025\)](#). Furthermore, while early-stage tasks benefit from well-defined and quantifiable metrics, later stages often involve complex, less formalized objectives such as semantic coverage robustness and sustained ontology refinement.

Addressing these limitations requires reframing later-stage OE not as autonomous LLM driven processes but as collaborative hybrid workflows. Future research should prioritize the development of hybrid architectures that integrate LLMs generated content with formal reasoning engines for constraint verification, the use of retrieval augmented generation techniques to maintain knowledge currency without full model retraining, and the design of human centered workflows in which LLMs assist experts in validation and refinement rather than operating independently. Such approaches would leverage the generative flexibility of LLMs while preserving the analytical discipline and domain expertise essential for sustainable and trustworthy ontology engineering.

5.2 Configuration workflows of LLMs in ontology development activities

Our findings show that LLMs can effectively assume multiple roles within OE tasks, notably as ontology engineers and domain experts. In these roles, LLMs support the automation of ontology construction and the enrichment of domain-specific knowledge, aiming at reducing the manual effort and transfer of domain-specific expertise traditionally required by ontology engineers.

In the surveyed literature, a consistent trend can be observed regarding model selection and application. GPT-series models are predominantly employed for reasoning-intensive tasks, whereas open-source and lightweight models (e.g., LLaMA, Mistral) are increasingly favored for tasks like ontology matching and conceptualization. This reflects a rapidly diversifying LLM ecosystem where model choice is strategically aligned with task demands. For instance, tuned variants of LLMs like GPT-3 have been used to produce ontological constructs for knowledge formalization, while smaller models such as Mistral-7B offer faster inference and perform efficiently on smaller or domain-specific datasets.

Prompting techniques have a significant impact on performance in all models. Zero-shot prompting is widely used for its efficiency in well-defined tasks, while template-based prompting is essential for enforcing strict output schemas such as OWL axioms and SPARQL queries. Role-based prompting enhances semantic reliability in specialized domains, and more advanced strategies including chain-of-thought reasoning, task decomposition, and iterative refinement are adopted in heterogeneous or

multi-stage workflows to stabilize outputs and improve accuracy. Furthermore, the interaction between prompting and model behavior is further demonstrated by the input and output configurations of the OE workflows. LLMs can handle unstructured, semi-structured, and fully structured data, producing outputs ranging from natural language descriptions and competency questions to executable queries and formal axioms. Although natural language remains the most common input modality, there is a clear shift toward structured formats that better constrain model behavior and ensure the production of machine-actionable results. These structured formats often operate in tandem with the prompting strategies discussed above, constituting an integrated configuration approach that enhances the reliability and usability of LLM-generated ontological artifacts.

Building on these foundations, the integration of LLMs introduces more conversational and iterative workflows compared to traditional methodologies. LLMs enable broader participation from engineers, domain experts, and non-specialists through natural language inputs, which the models transform into ontology fragments, refinements, or validation feedback. This shift increases flexibility, accelerates development cycles, and improves the scalability and accessibility of OE practices.

Despite these advantages, several limitations remain. LLMs require substantial computational resources for access and fine-tuning, which restricts their scalability [Hoffmann et al. \(2022\)](#); [Treviso et al. \(2023\)](#). Their generalization across specialized domains is often poor unless guided by carefully designed prompts, and without such guidance they may produce incomplete or semantically irrelevant outputs [Barman et al. \(2024\)](#). Parameter adaptation methods, including full fine-tuning and parameter-efficient approaches such as Low-Rank Adaptation (LoRA), still demand considerable human expertise for data preparation, supervision, and quality control, thereby further increasing costs and resource limitations [Wang et al. \(2025\)](#). Compared with formal logic systems [Baader et al. \(2017\)](#); [Heindorf et al. \(2022\)](#), LLM reasoning abilities remain shallow, and issues such as hallucinations, limited transparency and violations of fundamental ontological constraints persist [Xu et al. \(2025\)](#); [Petroni et al. \(2019\)](#); [West et al. \(2022\)](#); [Huang et al. \(2025\)](#). These shortcomings require external validation, post-processing, and expert correction to ensure logical and semantic soundness.

Notably, only four studies in our review involve human participants in LLM-based OE tasks, revealing a clear gap in current research. Human experts remain essential because LLMs often struggle to accurately interpret specialized knowledge. Expert review and iterative validation are therefore necessary throughout OE tasks to ensure the accuracy, clarity, and overall reliability of the outputs. The limited use of human participation can be attributed to methodological and resource-related constraints, such as the high cost of involving experts participation, the difficulty in standardizing human-involved interaction workflows and the prevailing tendency to prioritize automation. Few studies that incorporate human input focus on tasks that require semantic judgment or complex reasoning, areas where LLMs remain less reliable. This pattern indicates that future research should integrate expert participation more systematically to maintain semantic and logical integrity and improve the reliability and usability of LLM-generated ontology output.

To address these limitations, a broader and more coordinated research agenda is required. Future work should emphasize hybrid neuro-symbolic architectures that integrate the generative capabilities of LLMs with the formal precision of symbolic reasoners, enabling continuous validation of logical constraints [Servantez et al. \(2024\)](#); [West et al. \(2022\)](#); [Hitzler et al. \(2022\)](#). Given the limited use of fine-tuning in current practice, an important direction is the development and adoption of parameter-efficient fine-tuning (PEFT) techniques [Wang et al. \(2025\)](#). Such approaches support more stable and focused adaptation of LLMs to ontological structures while avoiding the substantial cost of full model retraining.

In parallel, more robust prompting strategies that can adapt to evolving knowledge contexts are needed to mitigate hallucinations and semantic drift [Zhang et al. \(2024b\)](#); [Liu et al. \(2025a\)](#). To improve the scalability of validation processes, automated verification pipelines should combine ontology checks with streamlined expert oversight. To address the human involvement gap, future methodologies should establish clear and systematic frameworks for integrating human validation into LLM-supported workflows, reducing the cost of expert participation and incorporating human judgment into evaluation practices.

Finally, enhancing the transparency of LLMs remains an open challenge to build trust and support the long-term maintenance of the OE based on LLMs. [Zhao et al. \(2024\)](#). For example, enabling models to explain how each answer is generated and to trace the provenance of every produced result would not only increase user trust but also facilitate the future reuse and maintenance of outputs from OE activities.

In general, achieving the full potential of LLMs in OE requires technical advances in both models and workflows, along with stronger human oversight, richer domain knowledge, and reliable formal verification.

5.3 Evaluation gaps and challenges for LLMs in ontology development activities

Our review shows that empirical validation has become a central practice in research on the use of large language models in ontology engineering. Nearly two thirds of the surveyed studies include full experimental evaluations, often built on open source domain ontologies in OWL or RDF that serve as expert curated benchmarks. Most papers employ quantitative, qualitative or combined evaluation methods, reporting metrics such as precision, recall, F1 score and semantic similarity, while complementing these with expert assessments of conceptual soundness and domain relevance. It is important to note that these evaluations usually assess entire pipelines rather than isolating the contribution of the large language model component. Since each study adopts its own baselines and datasets, direct comparisons across papers are rarely meaningful. However, evaluation practices consistently indicate that the use of large language models increases automation and often improves task performance across several stages of the ontology engineering lifecycle.

Across the reviewed studies, we also observe a growing use of publicly available datasets, which supports the development of more reproducible evaluation frameworks. Shared ontologies increasingly function as common baselines that later research can replicate or extend, and several studies employ gold standard datasets to ensure fairness and comparability. Early efforts toward standardized and transparent evaluation protocols have begun to emerge. Initiatives such as the OAEI ¹² and LLMs4OL [Giglou et al. \(2024\)](#) challenge explicitly define datasets, subtasks, and evaluation metrics, marking a move toward greater consistency and reproducibility within the field. From a methodological perspective, quantitative evaluations provide scalable, reproducible and transparent measurements of system performance [Liu \(2011\)](#); [Ioannidis and Maniadis \(2024\)](#). Qualitative assessments by domain experts capture semantic coherence, contextual relevance, and conceptual correctness that numerical metrics often overlook [Denzin et al. \(2006\)](#); [Patton \(2014\)](#); [Parfenova et al. \(2025\)](#). Integrating both forms of evaluation combines statistical rigor with semantic depth, thereby helping to ensure that the resulting ontologies are not only formally sound but also contextually meaningful and usable.

¹²<https://oaei.ontologymatching.org/>

Despite these advances, several limitations remain. First, evaluation methods are highly inconsistent, as most studies define their own tasks, datasets, metrics, and benchmarks. This lack of uniformity makes the results difficult to compare, and even minor differences in cue design or corpus selection can lead to discrepancies. More fundamentally, a coherent evaluation framework has yet to be established in the field. In addition, many studies do not standardize task definitions or input and output formats, which further complicates comparisons across different works. The lack of benchmark datasets for evaluating different ontology engineering tasks and the absence of clear and comprehensive evaluation metrics continue to constrain the development of the LLM-based OE community. Another important limitation is that the performance of LLMs is often conflated with the behavior of the entire pipeline. Many studies assess only the final output, making it difficult to identify the model's actual strengths and weaknesses. Although the use of both quantitative metrics and expert evaluations has improved current practice, challenges remain. Quantitative metrics do not capture deeper semantic or domain specific nuances, and qualitative assessments are time consuming [Queirós et al. \(2017\)](#), require expertise and introduce subjectivity, which limits scalability.

To address these limitations, future research should prioritize the development of standard evaluation protocols for LLMs-based based OE. A first step is the creation of unified benchmarks with clearly defined datasets, tasks and metrics that enable consistent comparisons across studies and across different OE activities. Standardizing task definitions and the formats of inputs and outputs would further reduce variability and support greater reproducibility. In addition, modular evaluation frameworks [Wu and Yu \(2024\)](#) are needed to separate the contribution of the large language model from other components of the pipeline. Such frameworks would help evaluate specific capabilities, identify failure cases and provide a clearer understanding of model behavior. Evaluation metrics should also be refined to capture semantic correctness, conceptual validity and domain relevance, rather than relying mainly on surface level accuracy measures. More systematic error analysis would help to identify and address model issues.

Finally, new evaluation strategies should be explored to improve both depth and scalability. These may include automated semantic validation tools, structured expert review procedures, and hybrid approaches that combine statistical measures with targeted human validation. Together, these efforts can contribute to a more robust and reliable evaluation ecosystem for LLMs-based OE.

5.4 Application domains of LLM-based ontology development

Across the reviewed studies, a clear trend emerges: while early applications were concentrated in healthcare and life sciences, the adoption of LLMs is rapidly expanding into domains such as cultural heritage, finance, emergency management, autonomous systems, and academic research. This highlights the inherent adaptability of models to address core ontology tasks from extraction and enrichment to validation and conceptual modeling in highly heterogeneous knowledge domains.

However, a cross-domain analysis reveals that the specific role of LLMs varies significantly from one domain to another. The uneven distribution of this progress provides important insight into the conditions that enable successful LLM–OE integration. For instance, Life sciences [Fathallah et al. \(2024b\)](#) and healthcare [Yang et al. \(2023\)](#) remain methodologically mature, supported by a powerful combination of factors such as abundant high-quality textual corpora (e.g., scientific literature, clinical documentation), an urgent need for interoperability, and, critically, the availability of mature, gold-standard ontologies such as SNOMED CT and the Gene Ontology (GO). These well-established resources offer the structural

scaffolding and authoritative examples needed to guide LLMs effectively, supporting tasks that include constraint validation and axiom generation.

In contrast, domains such as finance, disaster response, and cultural heritage often lack mature vocabularies and established development workflows. In these settings, LLMs are used less for refining existing ontologies and more for constructing domain knowledge from the beginning, including tasks such as knowledge extraction, conceptual modeling and ontology completion. Examples range from interpreting regulatory documents for financial ontologies (FIBO) to synthesizing search and rescue procedures in SAR ontology development. These studies show that LLMs can extract useful information from domain-specific resources, and that expert validation helps improve the quality of the results. With access to large amounts of unstructured text, LLMs support domain experts in transforming natural language descriptions into initial conceptual structures.

LLMs have been consistently used as intermediaries that bridge unstructured text and formal representations, although their efficacy remains contingent upon the clarity of target schemas. Therefore, robust domain-specific adaptation remains a significant challenge [Mai et al. \(2024\)](#). Models trained on general corpora often struggle with specialized terminologies and evolving knowledge structures, leading to semantic imprecision. Furthermore, scalability issues arise because LLMs, being statically trained, struggle to dynamically incorporate new knowledge without retraining, which restricts their long-term applicability [Du et al. \(2024\)](#). Consequently, ensuring formal consistency in regulated domains still requires substantial expert validation [Perera and Liu \(2024\)](#).

To address these limitations, future research should focus on improving the ability of LLMs to adapt to specialized and evolving knowledge domains. This involves developing methods that support the creation and refinement of domain specific vocabularies, schema templates and conceptual patterns, particularly in areas where consolidated ontologies are not yet available. At the same time, more effective mechanisms for integrating iterative expert feedback are needed so that domain specialists can actively shape and validate emerging conceptual structures throughout the development process. To ensure the long term applicability and accuracy of LLMs driven systems, techniques for dynamic knowledge updating and domain aware adaptation are also essential. This includes continued advancement of continual learning strategies [Shi et al. \(2025\)](#) and dynamic update mechanisms [Fan et al. \(2024\)](#) that enable models to incorporate new terminology, regulatory changes and evolving domain understanding without requiring complete retraining.

By advancing these directions, the community can better leverage the generative scalability of LLMs while ensuring that the resulting ontological knowledge remains precise, reliable, and sustainable across domains with different levels of knowledge maturity.

6 Conclusion

Our study employs a systematic literature review methodology to examine the technical applications and current state of LLMs in ontology OE. After searching multiple academic databases for literature published between 2018 and 2024 using keywords related to LLMs and OE, 30 papers covering 41 independent experiments were selected through a multi-stage screening process. It should be noted that earlier Transformer-based studies not explicitly identified as language models may fall outside the scope of this review. Four research questions (RQs 1–4) were formulated around the dimensions of LLM involvement in ontology development, focusing on supported core activities, technical implementation

methods, performance evaluation strategies, and application domains. Key information was systematically extracted, including research context, details of LLM usage (roles, model types, prompting strategies, input/output formats, if human involved in OE tasks), evaluation settings, and target domains.

Across the 41 examined studies, LLMs show clear strengths in early and middle stages of ontology development, especially in domain conceptualization, requirements specification, and ontology implementation. Models such as GPT and LLaMA, often used with zero-shot, template-based, or role-based prompts, can generate competency questions, formal axioms, and documentation. In these settings, they effectively take on responsibilities traditionally carried out by ontology engineers or domain experts. Their use in fields such as healthcare, cultural heritage, and autonomous systems illustrates the broad adaptability of current LLM-based approaches.

Although these findings highlight significant potential, several limitations remain. The support provided by current LLMs throughout the ontology lifecycle is uneven and subsequent activities, such as documentation and long-term maintenance, receive comparatively little attention. Their reasoning remains shallow, often leading to hallucinated facts and limited transparency [Bakker et al. \(2024\)](#); [Manda \(2025\)](#), which requires expert correction to ensure logical and semantic soundness. Evaluation practices also present substantial difficulties. Existing studies rely on heterogeneous tasks, datasets, and metrics, leading to inconsistent and often incomparable results. Current evaluation measures capture only part of the semantic or conceptual quality of the generated content, and the lack of unified and contamination-free benchmark datasets restricts systematic comparison between studies [Paulheim \(2025\)](#).

These limitations are particularly pronounced in application domains that lack mature and stable ontological resources. In such contexts, vocabularies and schemas are still evolving, making it difficult for LLMs to interpret specialized terminology and preserve semantic consistency. Their static training further limits the timely incorporation of newly emerging knowledge, and in regulated or safety-critical settings, expert validation remains essential to ensure correctness.

Given these challenges, several research directions have become urgent:

- **Lifecycle Coverage Expansion:** Extend LLM applications to underrepresented ontology lifecycle stages, particularly documentation, maintenance, to ensure long-term sustainability and continuous evolution of ontology development.
- **Hybrid Neuro-Symbolic Reasoning:** Develop hybrid systems that integrate LLM-generated content with formal logic validation, including OWL reasoning, ontology constraint checking, and semantic consistency verification, improving semantic accuracy, maintaining constraint consistency, and reducing hallucinations.
- **Enhancing LLM Adaptability:** Improve prompt methods and reduce the reliance on structured inputs to make LLMs more adaptable in OE tasks. Using parameter-efficient fine-tuning (PEFT) can further help models adjust to ontological structures without the high cost of full retraining.
- **Standardized Evaluation Frameworks:** Establish reproducible benchmarks based on expert-curated and publicly documented datasets, and evaluation metrics that combine quantitative measures with expert validation. Such expert-supported benchmarks are essential for reliably evaluating LLM-based OE systems, coping for dataset contamination and for ensuring fair comparisons across different methods, ultimately contributing to a more robust and trustworthy evaluation ecosystem.

- **Continuous Learning and Dynamic Adaptation:** Develop domain-adaptive LLMs that can integrate evolving knowledge without requiring full retraining. This requires effective mechanisms for dynamic knowledge updates and domain-aware adaptation, supported by advances in continuous learning and dynamic update methods. These improvements help models maintain scalability and relevance in dynamic domains.

The dispersed nature of the reviewed tasks reflects the early stage of the development of LLM-based OE rather than the methodological inconsistency. As the field matures, research is likely to converge toward more unified frameworks, shared resources, and standardized workflows.

By addressing these challenges, LLMs may progress from task specific assistants to reliable collaborators in ontology engineering, supporting scalable, transparent, and high quality knowledge representation across different domains. Achieving this vision will require not only technical innovation, but also stronger methodological foundations, richer models of human and model interaction, and robust community standards.

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Zhang S, Dong L, Li X, Zhang S, Sun X, Wang S, Li J, Hu R, Zhang T, Wang G et al. (2023a) Instruction tuning for large language models: A survey. *ACM Computing Surveys* DOI:10.1145/3777411.

Zhang Y, Yang H, Wang H and Zhao J (2024b) Fast adaptation via prompted data: An efficient cross-domain fine-tuning method for large language models. In: *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*. pp. 7117–7132.

Zhang Z, Zhang A, Li M, Zhao H, Karypis G and Smola AJ (2023b) Multimodal chain-of-thought reasoning in language models. *Trans. Mach. Learn. Res.* .

Zhao H, Chen H, Yang F, Liu N, Deng H, Cai H, Wang S, Yin D and Du M (2024) Explainability for large language models: A survey. *ACM Transactions on Intelligent Systems and Technology* 15(2): 1–38. DOI:10.1145/3639372.

Zheng M, Pei J, Logeswaran L, Lee M and Jurgens D (2024) When “a helpful assistant” is not really helpful: Personas in system prompts do not improve performances of large language models. In: *Findings of the Association for Computational Linguistics: EMNLP 2024*. DOI:10.18653/v1/2024.findings-emnlp.888.

7 Appendix

This appendix presents additional material supporting the main text, including extended tables and detailed data referenced throughout the study.

7.1 LLM-supported Ontology Development Activities

Table 2 provides a comprehensive mapping of how LLMs contribute to specific ontology engineering activities across the 41 reviewed studies. Each row represents one distinct studies and several studies might belong to the same paper, that is, for the cases in which one paper uses LLMs to support more than one activity. The table highlights the role, model used, input and output formats, and whether human participants were involved in the LLMs supported component.

Table 2. Details of LLM-supported ontology engineering activities, including the assigned roles of LLMs, model types used, input formats, generated outputs, and whether human involvement was required (indicated as YES/NO).

Resource	Role	Model	Prompt	Inputs	Outputs	Human involved
Requirements Specification – Functional Requirements Writing						
Fathallah et al. (2024a)	Ontology Engineer	GPT-3.5 LLaMA PaLM	Few-shot Role-based CoT	Natural language text	Natural language text	NO
Antia and Keet (2023)	Ontology Engineer	T5	N/A	Natural language text	CQs	NO
Requirements Specification – CQ Reverse Engineering						
Rebboud et al. (2024a)	Domain Experts	Not mentioned	N/A	Ontologies	CQs	NO
Alharbi et al. (2024a)	Ontology Engineer	GPT-3.5-turbo GPT-4 LLaMA2	Zero-shot	Triples	CQs	YES
Ciroku et al. (2024a)	Ontology Engineer	MiniLM T5 SBERT	Zero-shot Iterative refinement	KGs	CQs	NO
Rebboud et al. (2024b)	Ontology Engineer	DPO ¹³ SOLAR ¹⁴ UNA ¹⁵ Zephyr β GPT-3.5 GPT-4	Zero-shot Few-shot Fine-tuned FusionNet_7Bx2_MoE_14B Fine-tuned SOLAR-10.7B-Instruct-v1.0 Fine-tuned Mistral-7B Fine-tuned Mistral-7B-v0.1	Ontologies	CQs	NO

¹³Truthful_DPO_TomGrc_FusionNet_7Bx2_MoE_13B

¹⁴SOLAR-10B-OrcaDPO-Jawade

¹⁵UNA-TheBeagle-7b-v1

Table 2

Resource	Role	Model	Prompt	Inputs	Outputs	Human involved
Alharbi et al. (2024b)	Ontology Engineer	GPT-3.5-turbo GPT-4 LLaMA-2-70B Mistral 7B Flan-T5-XL	Zero-shot Role-based Template-based	Triples	CQs	NO
Requirements Specification – Requirement Formalization						
Rebboud et al. (2024a)	Ontology Engineer	Not mentioned	N/A	Ontologies and CQs	Queries	NO
Tufek et al. (2024)	Ontology Engineer	ChatGPT	Zero-shot Template-based	Natural language text or CQs	SPARQL Queries	NO
Kholmska et al. (2024)	Ontology Engineer	ChatGPT Bard	Zero-shot Template-based Role-based Iterative refinement	Concepts	SPARQL Queries	NO
Ontology Implementation – Conceptualization						
Rebboud et al. (2024a)	Domain Experts	Not mentioned	N/A	CQs	Ontologies	NO
Goyal et al. (2024)	Ontology Engineer	LLaMA3 GPT-4o Mistral	Zero-shot Few-shot	Natural language text	Binary decision	NO
Coutinho (2024)	Ontology Engineer	Not mentioned	Zero-shot Few-shot CoT	Natural language text	Summarization	NO
Kholmska et al. (2024)	Step 2: Ontology Engineer Step 3: Ontology Engineer	Step 2: ChatGPT, Bard Step 3: ChatGPT, Bard	Zero-shot Template-based Role-based Iterative refinement	Step 2: Natural language text Step 3: Natural language text	Step 2: Classes Step 3: Concepts	Step 2: NO Step 3: NO
Dong et al. (2024)	Domain Expert, Ontology Engineer	GPT-3.5 LLaMA2 FLAN-T5 GPT-4	Zero-shot Template-based Fine-tuned PLM	Natural language text, Ontologies	Natural language text	NO
Babaei Giglou et al. (2023)	Ontology Engineer	BERT, BLOOM LLaMA GPT-3 GPT-3.5 GPT-4 BART Flan-T5	Zero-shot	Task A: Natural language text, lexical term Task B: Natural language text Task C: Natural language text	Task A: Term type Task B: Binary decision Task C: Binary decision	NO
Toro et al. (2024)	Ontology Engineer	GPT-4 GPT-3.5-turbo	Few-shot Template-based	Term	JSON or YAML	NO
Pisu et al. (2024)	Ontology Engineer	BERT	Fine-tuned SciBERT	Nature language text	Relationships	NO
Ontology Implementation – Encoding						
Doumanas et al. (2024)	Ontology Engineer	GPT-4 GPT-3.5 Bard LLaMA	Zero-shot Template-based Iterative refinement	Phase 1: Natural language text Phase 2: Domain documents Phase 3: Natural language text and CQs	Phase 1: Ontologies Phase 2: Ontologies Phase 3: Ontologies	YES
Fathallah et al. (2024a)	Ontology Engineer	GPT-3.5 LLaMA PaLM	Few-shot Role-based CoT	Natural language text	CQs, Triples and Ontologies	NO
Caufield et al. (2024)	Ontology Engineer	OntoGPT	Zero-shot	Natural language text	Ontologies	NO
Eells et al. (2024)	Ontology Engineer	GPT-4	Zero-shot Template-based	Natural language text	Natural language text	NO

Table 2

Resource	Role	Model	Prompt	Inputs	Outputs	Human involved
Saeedizade and Blomqvist (2024)	Ontology Engineer	GPT-3.5 GPT-4 Bard LLaMA-7B LLaMA-13B LLaMA2-70B Alpaca Falcon-7B Falcon-7B-Instruct WizardLM Alpaca-LoRA	Zero-shot CoT GoT	CQs	Ontologies	NO
Mateiu and Groza (2023)	Ontology Engineer	GPT-3 Davinci model	Zero-shot Few-shot Fine-tuned GPT-3	Natural language text	Axioms	NO
Tang et al. (2023)	Ontology Engineer	ChatGPT	Zero-shot Template-based Iterative refinement Decomposition	Natural language text	Ontologies, JSON and Triples	NO
da Silva et al. (2024)	Ontology Engineer	GPT-4, Turbo4, Claude3, Gemini Pro	Zero-shot Template-based Few-shot One-shot	Natural language text, Ontologies	Ontologies	NO
Ontology Development – Ontology Matching and Reuse						
Zamazal (2024)	Domain Experts	GPT-4o	Zero-shot	Natural language text and verbalized candidates	Binary decision	NO
Kholmska et al. (2024)	Ontology Engineer	ChatGPT Bard	Zero-shot Template-based Role-based Iterative refinement	Step 4: Natural language text Step 6: Concepts, Ontologies, Natural language text	Step 4: Documentation Step 6: Mapping	NO
Hertling and Paulheim (2023)	Ontology Engineer	LLaMA	Zero-shot Few-shot	Ontologies and Natural language text	Mapping	NO
He et al. (2023)	Ontology Engineer	Flan-T5-XXL GPT-3.5-turbo	Zero-shot Template-based	Natural language text	Binary decision	NO
Norouzi et al. (2023)	Ontology Engineer	ChatGPT	Zero-shot	Natural language text	Mapping	NO
Ontology Development – Ontology Evaluation						
Tsaneva et al. (2024)	Domain Experts, Human Evaluator	GPT-4	Few-shot Zero-shot	Natural language text	Axioms	NO
Kholmska et al. (2024)	Ontology Engineer	ChatGPT Bard	Zero-shot Template-based Role-based Iterative refinement	Step 5: Ontologies	Step 5: Natural language text	NO
Fathallah et al. (2024a)	Domain Expert, Ontology Engineer	GPT-3.5 LLaMA PaLM	Few-shot Role-based CoT	Natural language text	Ontologies and Axioms	NO
Zhang et al. (2025)	Ontology Engineer	GPT-3	One-shot Few-shot Iterative refinement	Ontologies and CQs	Binary decision	YES
Ontology Publication – Documentation						
Bischof et al. (2024)	Domain Experts	Mistral 7B	Zero-shot Template-based Role-based	Natural language text	Terms	NO
Rebboud et al. (2024a)	Domain Experts	Not mentioned	N/A	Ontologies	Documentation	NO

Table 2

Resource	Role	Model	Prompt	Inputs	Outputs	Human involved
Kholmska et al. (2024)	Ontology Engineer	ChatGPT Bard	Zero-shot Template-based Role-based Iterative refinement	Step 9: Ontology Extensions, Natural language text	Step 9: Documentation	NO
Fathallah et al. (2024a)	Ontology Engineer	GPT-3.5 LLaMA PaLM	Few-shot Role-based CoT	Natural language text, Ontologies	Documentation	NO
Giri et al. (2024)	Domain Experts, Ontology Engineer	T5	Fine-tuned T5	Terms	Documentation	NO
Maintenance – Bug Issue						
Kholmska et al. (2024)	Domain Expert	ChatGPT Bard	Zero-shot Template-based Role-based Iterative refinement	Step 8: Natural language text	Step 8: Natural language text	YES

7.2 Experimental Setup and Evaluation Overview

Table 3 summarizes the experimental validation practices across all 41 reviewed studies. It records whether an experiment was performed, provides open-source access links when available, identifies the datasets utilized, and details the evaluation methodology (quantitative, qualitative, or mixed by both) along with the specific metrics employed. By including dataset sources and tool repositories, the table aims to support reproducibility and offers insights into the evaluation rigor and maturity within the field.

Table 3. Summary of experiments, data sources, evaluation types, and evaluation metrics used in LLM-supported ontology engineering studies.

Paper resource	Experiment	Data source	Evaluation type	Evaluation metric
Requirements specification – Functional requirements writing				
Fathallah et al. (2024a)	YES ³⁷ , a test ³⁷	Wine	N/A	N/A
Antia and Keet (2023)	YES ¹⁶	Covid19 articles ¹⁷	Qualitative	Human comment
Requirements specification – CQ Reverse Engineering				
Rebboud et al. (2024a)	N/A	DOREMUS, Polifonia, DemCare, Odeuropa, NORIA-O, FIBO	Quantitative	Cosine Similarity
Ciroku et al. (2024a)	YES ¹⁸	WDV ¹⁹	Quantitative	BLEU score
Rebboud et al. (2024b)	YES ³⁶	DOREMUS, Polifonia, Dem@Care, Odeuropa, NORIA-O, FIBO	Quantitative	Cosine Similarity
Alharbi et al. (2024a)	YES	VideoGame, Dem@care, VICINITY Core, African Wildlife	Hybird	Number of CQs, Precision, Recall, F1
Alharbi et al. (2024b)	YES	Video Game, VICINITY Core; and Dem@care, Solar System Ontology	Quantitative	Precision, Recall, F1
Requirements specification – Requirement formalization				
Rebboud et al. (2024a)	N/A	DOREMUS, Polifonia, DemCare, Odeuropa, NORIA-O, FIBO	Quantitative	Tree Edit Distance
Tufek et al. (2024)	YES ²⁰	Smart Applications REference, OPC UA Robotics	Quantitative	Precision, Recall, F1
Kholmska et al. (2024)	N/A	OntoDM	Quantitative	Model Consistency Error Rate Reduction Coverage of Relevant Concepts
Ontology implementation – Conceptualization				
Rebboud et al. (2024a)	N/A	DOREMUS, Polifonia, DemCare, Odeuropa, NORIA-O, FIBO	Quantitative	Precision, Recall, F1, Accuracy, Consistent Ontology
Goyal et al. (2024)	YES ²¹	Task B: GeoNames, Schema.org, UMLS, GO Task C: UMLS	Quantitative	Precision, F1-score

Table 3

Paper resource	Experiment	Data source	Evaluation type	Evaluation metric
Coutinho (2024)	N/A	UFO	Hybrid	Time, Model Quality Metrics, User Satisfaction, Domain Experts Feedback
Kholmska et al. (2024)	N/A	OntoDM	Quantitative	Inter-Model Consistency, Error Rate Reduction, Coverage of Relevant Concepts
Dong et al. (2024)	YES ²²	MM-S14-Disease, MM-S14-CPP	Quantitative	InRank@k, InRecall@k
Babaei Giglou et al. (2023)	YES ²³	WordNet, GeoNames, UMLS, National Cancer Institute, MEDCIN, SNOMEDCT US, Schema.org	Quantitative	MAP@K, F1-score
Toro et al. (2024)	YES ²⁴	Cell Ontology, UBERON, GO, Human Phenotype Ontology, Mammalian Phenotype Ontology, MONDO, Environment Ontology, Food Ontology, Ontology of Biomedical Investigations, Ontology of Biological Attributes	Quantitative and Qualitative	Accuracy, Recall, F1, Manual Assessment
Pisu et al. (2024)	YES ²⁵	Computer Science Ontology	Quantitative	Accuracy, Precision, Recall, F1
Ontology implementation – Encoding				
Doumanas et al. (2024)	YES ²⁶	Wildfire	Hybrid	Analysis of False Positives Precision, Recall, F1-score
Fathallah et al. (2024a)	YES, a test ³⁷	Wine	N/A	N/A
Caufield et al. (2024)	YES ²⁷	GO, EMAPA, MONDO Disease Ontology	Quantitative	F1, Precision, Recall
Eells et al. (2024)	YES ²⁸	101 nouns from COCA	N/A	N/A
Saeedizade and Blomqvist (2024)	YES ²⁹	Music, Theater, Hospital	Qualitative	Score Evaluation
Mateiu and Groza (2023)	N/A	150 sentences	N/A	N/A
Tang et al. (2023)	N/A	OpenXOntology	N/A	N/A
da Silva et al. (2024)	YES ³⁰	CaSk	Quantitative and Qualitative	Mean Error Score
Ontology development – Ontology matching and reuse				
Zamazal (2024)	YES ³¹	EDOAL, Manchester from OAIE	Hybrid	Precision, Relaxed Precision, Recall
Kholmska et al. (2024)	N/A	OntoDM	N/A	N/A
Hertling and Paulheim (2023)	YES ³²	Ontologies from OAIE	Quantitative	Precision, Recall, F1, Size, Time
He et al. (2023)	YES ³³	NCIT-DOID, SNOMED-FMA	Quantitative	Precision, Recall, F1, Hits, MRR, RR
Norouzi et al. (2023)	YES	Ontologies from OAIE	Quantitative	Precision, Recall, F1
Ontology development – Ontology evaluation				
Tsaneva et al. (2024)	YES	Pizza Ontology	Hybrid	Accuracy, Precision, Recall, F1, Majority Vote Aggregation
Kholmska et al. (2024)	N/A	OntoDM	N/A	N/A
Fathallah et al. (2024a)	YES, a test ³⁷	Wine	N/A	N/A
Zhang et al. (2025)	YES ³⁴	Music Meta	Qualitative	Feedback Scores
Ontology publication – Documentation				
Bischof et al. (2024)	N/A	N/A	Qualitative	Expert reviews
Rebboud et al. (2024a)	N/A	DOREMUS, Polifonia, DemCare, Odeuropa, NORIA-O, FIBO	Quantitative	Cosine Similarity
Kholmska et al. (2024)	N/A	OntoDM	Quantitative	Inter-Model Consistency, Error Rate Reduction, Coverage of Relevant Concepts
Fathallah et al. (2024a)	YES, a test ³⁷	Wine	N/A	N/A

Table 3

Paper resource	Experiment	Data source	Evaluation type	Evaluation metric
Giri et al. (2024)	YES ³⁵	GO	Quantitative and Qualitative	Correlation with Embedding Scores, Confidence Scores
Maintenance – Bug issue				
Kholmska et al. (2024)	N/A	OntoDM	Quantitative	Inter-Model Consistency, Error Rate Reduction, Coverage of Relevant Concepts

7.3 Application Domains of LLMs in OE

Table 4 presents a categorization of application domains where LLMs are used in ontology development. For each domain, we list representative ontologies and the key studies that utilized them across our review. This offers insights into how LLM applications vary across domains such as healthcare, cultural heritage, and autonomous systems.

Table 4. Key application domains, example ontologies, and representative studies using LLMs for ontology development.

Application Domain	Example Ontologies	Key Papers
Healthcare & Medicine	DemCare, SNOMED CT, UMLS	Tsaneva et al. (2024), He et al. (2023)
Cultural Heritage	DOREMUS, Polifonia, Odeuropa	Rebboud et al. (2024a,b), Zhang et al. (2025)
Finance & Banking	FIBO	Rebboud et al. (2024a,b)
Search & Rescue (SAR)	SAR Ontology	Doumanas et al. (2024)
Biology & Life Sciences	Gene Ontology (GO), MONDO	Giri et al. (2024), Caufield et al. (2024)
Autonomous Driving	Road traffic ontologies	Tang et al. (2023)
Education & Research	Computer Science Ontology	Pisu et al. (2024)
Food & Agriculture	FoodOn	Caufield et al. (2024)

7.4 Ontology Datasets Used Across Studies

Table 5 lists all experiment datasets utilized in the reviewed studies, with their corresponding names, access URLs, and associated domains. This compilation supports transparency and facilitates future replication or comparative benchmarking using the same datasets.

Table 5. Summary of experiment datasets used across the reviewed studies, including their names, access links, and corresponding application domains.

Acronym Name	Full Name	URL	Domain
African Wildlife	African Wildlife Ontology	http://www.meteck.org/teaching/ontologies-/AfricanWildlifeOntology1.owl	Ecology
CaSk	Capability and Skill Ontology	https://github.com/CaSkade-Automation/CaSkMan	Robotics
CL	Cell Ontology	https://github.com/obophenotype/cell-ontology	Anatomy
CSO	Computer Science Ontology	https://cso.kmi.open.ac.uk/home	Computer Science
DemCare	Dementia Care Ontology	https://demcare.eu/ontologies	Healthcare
DOREMUS	Music Ontology	http://data.doremus.org/ontology	Arts
EMAPA	Mouse Developmental Anatomy	https://obofoundry.org/ontology/emapa.html	Anatomy
ENVO	Environment Ontology	https://github.com/EnvironmentOntology/envo	Environment
FIBO	Financial Industry Business Ontology	https://github.com/edmcouncil/fibo	Business
FOODON	Food Ontology	https://github.com/FoodOntology/foodon	Food
GO	Gene Ontology	http://geneontology.org	Biology
HP	Human Phenotype Ontology	https://github.com/obophenotype/human-phenotype-ontology	Phenotype
MONDO	Mondo Disease Ontology	https://github.com/monarch-initiative/mondo	Disease
MP	Mammalian Phenotype Ontology	https://github.com/obophenotype/mammalian-phenotype-ontology	Phenotype
MusicMeta	Music Metadata Ontology	https://w3id.org/polifonia/ontology/music-meta	Music
NORIA-O	Norwegian AI Ontology	https://w3id.org/noria	AI
OAIE	Ontology Alignment Evaluation Initiative	https://oaei.ontologymatching.org	Benchmark

¹⁶<https://github.com/pymj/AgOCQs>

¹⁷<https://github.com/pymj/AgOCQs/tree/main/AgOCQs/inputText>

¹⁸<https://github.com/King-s-Knowledge-Graph-Lab/revont>

¹⁹<https://github.com/gabrielmaia7/WDV>

²⁰<https://github.com/Siemens-OKE/llm-query-pipeline>

²¹<https://drive.google.com/drive/folders/1vRynlNH6LouIvcIlymHsm6DwYKSOUoAa>

²²<https://github.com/KRR-Oxford/LM-ontology-concept-placement>

²³<https://github.com/HamedBabaei/LLMs4OL>

²⁴<https://github.com/monarch-initiative/dragon-ai-results>

²⁵<https://github.com/aleessiap/LeveragingLMforGeneratingOntologies>

²⁶<https://github.com/dimitrisdoumanas19/New-Experiments-LLMs.git>

²⁷<https://github.com/monarch-initiative/ontogpt>

²⁸<https://github.com/kastle-lab/commonsense-micropatterns>

²⁹<https://github.com/LiUSemWeb/LLMs4OntologyDev-ESWC2024>

³⁰<https://github.com/CaSkade-Automation/llm-capability-generation>

³¹<https://github.com/OndrejZamazal/ComplexOntologyMatching-SEMANtICS2024>

³²https://figshare.com/articles/code/OLaLa_for_OAEI

³³<https://github.com/KRR-Oxford/LLMap-Prelim>

³⁴<https://github.com/King-s-Knowledge-Graph-Lab/OntoChat>

³⁵<https://github.com/kiharalab/GO2Sum>

Table 5

Acronym Name	Full Name	URL	Domain
OBA	Ontology of Biological Attributes	https://github.com/obophenotype/biological-attributes-ontology	Attributes
OBI	Ontology for Biomedical Investigations	https://github.com/obi-ontology/obi	Methodology
Odeuropa	Olfactory Heritage Ontology	https://odeuropa.eu	Cultural Heritage
OntoDM	Ontology of Data Mining	https://lod-cloud.net/dataset/bioportal-ontodm	Data Science
OpenXOntology	Open Exchange Ontology	https://openxontology.org	Business
OPC-UA	OPC Unified Architecture	https://github.com/OPCFoundation/UA-Nodeset	Industrial
Polifonia	Polifonia Ontology Network	https://github.com/polifonia-project	Music
SAREF	Smart Appliances Reference Ontology	https://saref.etsi.org	IoT
UBERON	Uberon Multi-species Anatomy Ontology	https://github.com/obophenotype/uberon	Anatomy
UFO	Unified Foundational Ontology	https://ontouml.readthedocs.io/en/latest/intro/ufo.html	Foundational
UMLS	Unified Medical Language System	https://www.nlm.nih.gov/research/umls	Medicine
VICINITY	IoT Core Ontology	http://iot.linkeddata.es/def/core	IoT
WDV	Web Data Vocabulary	https://github.com/gabrielmaia7/WDV	Web
Pizza	Pizza Ontology	https://protege.stanford.edu/ontologies/pizza-/pizza.owl	Food
NCIT	National Cancer Institute Thesaurus	https://bioportal.bioontology.org/ontologies/NCIT	Oncology
DOID	Human Disease Ontology	https://bioportal.bioontology.org/ontologies/DOID	Disease
SNOMED CT	Systematized Nomenclature of Medicine Clinical Terms	https://www.snomed.org/	Medicine
FMA	Foundational Model of Anatomy	https://bioportal.bioontology.org/ontologies/FMA	Anatomy
MEDCIN	MEDCIN Ontology	https://www.sciencedirect.com/topics/nursing-and-health-professions/medical-ontology	Medicine
SNOMEDCT US	SNOMED CT United States Edition	https://www.nlm.nih.gov/healthit/snomedct/	Medicine
Schema.org	Schema.org Vocabulary	https://schema.org/	Web
Video Game Ontology	Video Game Ontology	https://vocab.linkeddata.es/vgo/	Entertainment
MM-S14-Disease/CPP	MM-S14-Disease/CPP Dataset	https://zenodo.org/records/10432003	Medicine
Wine Ontology	Wine Ontology	https://github.com/UCDavisLibrary/wine-ontology.owl	Food

³⁶ <https://github.com/D2KLab/11m4ke>

³⁷ <https://github.com/andreamust/NEON-GPT>