Ontogenia: Ontology Generation with Metacognitive Prompting in Large Language Models

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Abstract. Recent advancements in Large Language Models (LLMs) have primarily focused on enhancing task-specific performances by experimenting with prompt design. Despite the proven effectiveness of Metacognitive Prompting (MP), its application in the field of ontology generation remains an uncharted territory. This study addresses this gap by exploring this prompting technique in supporting the ontology design process, particularly with GPT-4, where this strategy has demonstrated consistent superiority over conventional and more direct prompting methods in recent research. Our methodology, named Ontogenia, employs a gold-standard dataset of ontology competency questions translated into SPARQL-OWL queries. This approach allows us to explore various types and stages of knowledge refinement using MP, while adhering to the eXtreme Design methodology, a well-established protocol in ontology design. Finally, the quality and performance of the resulting ontologies are assessed using both standard ontology quality metrics and evaluation by an ontology expert. This research aims to enrich the discussion on methods of ontology generation driven by LLMs by presenting concrete results on the use of metacognitive prompting and ontology design patterns.

Keywords: Ontology Engineering · Competency Questions · Large Language Models · Metacognitive Prompting

1 Introduction and Related Work

Ontology design involves conceptualizing and formalizing knowledge networks for semantic technologies. Methodologies like eXtreme Design (XD) [2] offer structured frameworks for ontology engineers, yet their complexity demands substantial expertise and resources. Manual curation and validation of ontological elements are labor-intensive, suggesting a need for intelligent automation. Large Language Models (LLMs), being able to effectively perform various natural language processing goals, present a compelling solution. More so, in the field of the so-called "Cognitive AI", which is now considered an essential prerequisite for the development of more advanced AI forms [7]. In particular, the Metacognitive Prompting (MP) technique [8], inspired by human introspective processes, encourages self-evaluation through the introduction of a series of steps, building and supposedly improving performance over other methods such as Chain of Thought. Derived from the field of cognitive psychology, metacognition concerns an individual's capacity to self-reflect and critically evaluate their cognitive processes [3, 6]. While traditional prompting might direct the LLM to simply create an ontology based on a set of parameters or data, MP involves asking the LLM to consider its own reasoning process, evaluate the credibility and reliability of the information it uses, and adapt its strategies based on this self-assessment, as shown by [9]. This could lead to more accurate and robust outcomes with respect to classic prompting techniques, as the model not only generates outputs but also critically analyzes its methods and decisions, much like the self-reflection and self-inquiry methodologies employed in recent studies to mitigate hallucinations and improve data handling [1]. This approach could effectively reduce errors and enhance the logical consistency of outputs, bringing them closer to human cognitive processes where reflection is crucial in learning and decision-making. Furthermore, incorporating Ontology Design Patterns can guide the process by injecting structured knowledge patterns that lend structure to the knowledge itself as a top-down approach. Starting from these studies, in this paper we define the Ontogenia methodology to explore the usage of LLMs for one of the most crucial and creative steps in ontology design methodologies: the actual specification and formalisation of an ontology (or module thereof) based on a specific set of requirements[3]. The main aim of this work is to advance the discussion on automated ontology generation using LLMs. The main contributions are:

- A methodology to test the efficacy of MP and its application in automated ontology generation;
- A framework to assess the influence of Ontology Design Patterns (ODPs) on the ontology generation process, and, more broadly, to incorporate the eXtreme Design methodology in LLM-assisted ontology generation;
- A qualitative and quantitative evaluation of this framework, which identifies both advantages and specific deficiencies in LLMs' generation of ontology features.

2 The Ontogenia methodology

The Ontogenia methodology outlines a concise yet comprehensive approach to ontology development through an iterative and incremental process.

Domain and CQ definition The dataset under consideration is derived from a recognized gold-standard used for testing and benchmarking in the field of competency questions research and ontology querying, detailed in [4]. For this study, a specific use case has been selected: the African Wildlife Ontology. This choice facilitates modeling a sufficiently broad domain with respect to the others in the dataset while simultaneously being able to use domain-specific ontology design patterns. The chosen subset comprises 14 distinct competency questions, providing a potentially comprehensive starting point for analysis.

Ontology Design Patterns selection Being readily available online, Ontology Design Patterns can be a valuable resource for facilitating transfer and analogy learning. In fact, they enable structured knowledge adaptation to new scenarios, a key component in MP where both shared commonsense knowledge and abstract reasoning are essential. This approach also helps maintain human involvement in the loop. The definition of the Ontology Design Patterns to reuse starts from the list of Content Ontology Design Patterns in the Ontology Design Patterns website[4]. From these, eight have been selected by ontology experts for their relevance to the domain and included in a dataset to be dynamically inputted to the prompt: *AgentRole, AquaticResources, Classification, Climatic Zone, Collection Entity, PartOf, Linnaean Taxonomy, SpeciesEat.* Collectively, these ODPs can provide a comprehensive foundation for answering the targeted competency questions, enabling a thorough exploration of animal-related topics in a systematic and informed manner.

Procedure and prompt design The procedure design was crafted through an iterative process, with each phase incrementally tested to evaluate the outcomes. This design strategy aims to amalgamate the MP technique with the eXtreme Design methodology [2], which requires the use of pre-selected competency questions—a collaborative effort between the ontology design team and domain experts. Additionally, it involves the selection, reuse, and integration of specific Content Patterns. This iterative approach, coupled with constant testing and reassessment, has ensured the procedure's alignment with the initial requirements. To bridge any gaps in the LLM's understanding of specific ontology features, these elements were explicitly incorporated into the procedure, enhancing its comprehensiveness and effectiveness.

The prompt design is meant to incorporate information about the procedure, eventual previous output, competency questions and patterns to be also added dynamically to the

[3] Data and code used for the work is available at this link: `https://anonymous.4open.science/r/Ontogenia-CAE4/README.md`

[4] `http://ontologydesignpatterns.org/wiki/Submissions:ContentOPs`

prompt on the basis of specific needs. A specification to not repeat itself and not send comments was added in order to refine the output. The resulting procedure is mapped to the MP five steps as shown in Table 1.

Table 1. Mapping between the Ontogenia methodology and the MP procedure.

MP stages	**Ontogenia stages**	**Description**
Comprehension clarification	1. Competency question understanding.	The LLM interprets the CQs, contextualizing them.
Preliminary judgement	2. Preliminary identification of the context. 3. Divide the competency question into subject, predicate, object, and predicate nominative.	Logical analysis supports class and property identification from CQs.
Critical evaluation	5. Starting from your knowledge, extend the ontology with these restrictions.	Reflect on CQs to add rules and restrictions, enhancing the model.
Decision confirmation	8. Confirm the final answer and explain the reasoning.	Justify the decision-making process.
Confidence assessment	9. Make a confidence evaluation and explanation, testing the ontology on instances.	Evaluate the process and test the model's correctness with specific instances.

Evaluation measures definition The definition of the evaluation is twofold. On the one hand, it involves an ontology engineer expert that analyzes the produced ontologies in terms of essential requirements such as required classes and object properties and usage of restrictions. On the other hand, in order to complement the expert analysis, it involves the Ontometrics service[5] and the OOPS! Ontology Pitfall Scanner [5].

Testing We use GPT-4 Turbo API (gpt-4-1106-preview[6]) as our backbone model, with greedy decoding. Because GPT has a token limit in output, we came up with a division of competency questions to be given one group at a time, and each time the previous output is provided in order not to have a repeating of classes and properties.

We conducted four trials to evaluate the effect of different inputs on ontology generation. Trial 1 used competency questions with a generic prompt, Trial 2 added ontology design patterns, Trial 3 involved only competency questions and MP, and Trial 4 combined competency questions with the prompting procedure and patterns. We tested both the original and thematically grouped questions by GPT. The total computation cost was $2.10. Experiment details are documented in a Github repository[7].

3 Results and discussion

Table 2 shows the metrics obtained using the OntoMetrics service for each case considered in the experiment. It can be seen that in our experiment the adoption of MP favors a richer formalisation. This is also evident from Table 3 that shows usage of a set of different types of axiom types across the test cases. At the same time, it should be noted that there are important limitations common to all the cases, such as the absence of property hierarchical relationships.

[5] `https://ontometrics.informatik.uni-rostock.de/ontologymetrics/`
[6] `https://openai.com/blog/new-models-and-developer-products-announced-at-devday`
[7] `https://anonymous.4open.science/r/Ontogenia-CAE4/ontology_design.log`

The pitfalls found by OOPS! were also analysed. Some issues are common to all the cases, as the lack of annotations (P08) and inverse relationships (P13)[8]. All the cases except case 3 contain at least a property that is defined with more than one domain or range (P19). This happens when the LLM generates multiple times the definition of an object property, with somewhat different domain/range values. It seems that the "intent" of the LLM would be to define the property over the union of the referenced classes, mirroring a common beginner's error in RDFS modelling. In the cases using patterns (2 and 4) an "untyped class" (P34) and "different naming conventions" (P22) are found. These are both due to the erroneous of an object property (`hasPart`) imported from a pattern but used as it was a class. Furthermore, in Case 1, no disjoint axioms are used (P10) and there are a couple of properties missing explicit domain/range declaration (P11)[9]. The ontology obtained in Case 3 is the only one featuring an ontology element, the `Plant` class, unconnected from the rest of the ontology. Nevertheless, Case 3 is the one having less pitfalls.

For what concerns basic metrics, Ontometrics shows a larger number of axioms when a pattern is used, along with a higher number of classes and object properties. Data properties are instead a weaker point, despite their use having been specified in the procedure.

According to the qualitative analysis by the ontology expert, while the LLM successfully identifies necessary classes and relevant subclasses, the generated ontologies exhibit numerous intrinsic and domain-related issues. Particularly problematic is the pairing of classes and properties. Properties like `eats` often possess overly specific domains and ranges, leading to the creation of unrelated properties such as `eatsPlant`, `eatsAnimal`, and `eatsPlantPart`. While simple restrictions in class definitions are generally correct, the classification of animals by diet consistently falls short. This shortfall is partly due to the ambiguity of terms like "carnivore" in biological contexts, where strict logical constraints are challenging to establish. This highlights the necessity for further research into the collaboration between ontology design teams and LLMs, opening avenues for exploring new directions.

Table 2. How Ontometrics base metrics vary between various test cases and the reference ontology. For each case, it is indicated whether the patterns or the MP have been used.

Ontometrics	**Case1 No pattern No MP**	**Case2 Pattern No MP**	**Case3 No pattern MP**	**Case4 Pattern MP**	**Reference Ontology**
Axioms count	49	119	64	118	108
Logical axioms count	26	74	36	76	56
Class count	14	17	14	21	31
Object property count	8	11	8	14	5
Data property count	0	2	3	2	0
Properties count	8	13	11	16	5
Individual count	1	19	0	11	0
DL expressivity	ALCROI	AL(D)	ALC(D)	ALCI(D)	SRI

The findings of this work suggest that while the use of Metacognitive Prompting and Ontology Design Patterns in LLM-driven ontology generation shows promise for richer formalization and a higher complexity of generated structures, significant issues persist. These include the lack of proper property hierarchies, annotation errors, and incorrect domain/range assignments, indicating that the current state of LLM-driven ontology tools may not yet be ready for real-world applications. However, these results provide valuable insights that can stimulate further discussion and drive refinements in both the methodology and implementation of LLMs in ontology design, potentially leading to more robust and accurate systems in the future. The outcomes from this initial work have prompted new questions: Can automated tools replace ontology experts for ontology validation? Can we achieve higher levels of accuracy in self-generated models? In the future, we aim to extend our research to other

[8] The lack of license information (P41) is also common to all the cases, but this is not an information to be expected from the LLM.

[9] Domain and range of those two properties are actually in part inferable because, errors aside, they are meant to be defined in relationship to other properties.

Table 3. Use of types of OWL axioms in various test cases. For each case it is indicated whether the patterns or MP were used.

Axiom type	**Case1 No pattern No MP**	**Case2 Pattern No MP**	**Case3 No pattern MP**	**Case4 Pattern MP**
owl:Ontology	Yes	Yes	Yes	Yes
owl:Class	Yes	Yes	Yes	Yes
owl:ObjectProperty	Yes	Yes	Yes	Yes
owl:DatatypeProperty	No	No	Yes	Yes
rdfs:domain	Yes	Yes	Yes	Yes
rdfs:range	Yes	Yes	Yes	Yes
rdfs:subClassOf	Yes	Yes	Yes	Yes
rdfs:subPropertyOf	No	No	No	No
owl:disjointWith	No	No	Yes	Yes
owl:equivalentClass	Yes	No	Yes	No
owl:Restriction	Yes	No	Yes	Yes
owl:imports	No	Yes	No	Yes

models of LLMs and expand the set of instructions and patterns employed in the procedure design, possibly including an automatic selection step by the LLM.

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Disclaimer

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