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A Survey on Ontologies' Adaptability and Interoperability

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Abstract**:** *Interoperability issues emerge due to differences in the sizes and expressive powers of ontologies. Although ontologies are expressive, they tend to lack flexibility. Research shows that specialized ontologies are not merely advantageous for a particular domain or goal; they also promote enhanced alignment, though certain ones can be difficult, particularly when handling certain kinds of specialized ontologies or during the integration process. However, due to changes in research, some ontologies are consistently growing, shrinking, or even evolving in their usage. Nonetheless, other specific ontologies are seldom employed. Additionally, we evaluated every category of specialized ontology in terms of its ease of alignment according to our assessment and current literature.*

Keywords**:** *Semantic Web, Ontologies, Linked Data, Context ontology, Ontology alignment.*

1. Introduction

First and foremost, it is worth mentioning that ontology is a philosophical field that studies the structure of objects along with their properties and relations [1]. Whereas in computer sciences, ontology can be referred to as "an explicit specification of a conceptualization" (G r u b e r [14]). Second, the formalization of an ontology, which involves defining concepts, categories, and their interrelationships, allows for the creation of meaningful relationships between entities that extend beyond predefined or static data models. This is particularly important in the context of linked data, where resources are identified by Uniform Resource Identifiers (URIs) such as Uniform Resource Locators (URLs) or location-independent Uniform Resource Names (URNs). The use of URIs enables the linking of data across disparate sources, allowing for dynamic connections to be made between previously isolated datasets. This approach not only facilitates the integration of information but also enriches it by establishing new relationships that can evolve over time, independent of the physical location of the resources. Nevertheless, benefiting from ontologies can be tricky and not evident, given the challenges that one can face when trying to incorporate them. On the one hand, ontologies are intended to represent knowledge in a broad and reusable way. Consider a patient with hypertension. A general healthcare ontology might link "hypertension" to a generic category like "cardiovascular diseases" and recommend broad treatments like "lifestyle changes" or "medication". However, in a nuanced scenario, A patient's age, comorbidities (like diabetes), and family history of heart disease would significantly influence treatment. Also, medication interactions with other drugs the patient is taking may be a critical consideration. This is mainly coming from design choices – not an inherent flaw in ontological representation. With proper modeling, ontologies can balance generality and precision, even in dynamic domains. In reality, many domains experience shifts in concepts and definitions based on time and context, amongst other things. On the other hand, some ontologies may lack interoperability due to standardization issues, given that different ontologies can use different ontological languages. For instance, one can be using OWL Lite and the other one OWL Full, which is highly expressive. Or the lack of interoperability can be due to the use of different top-level ontologies as the base of domain ontologies (e.g., using DOLCE versus Basic Formal Ontology (BFO)). Or this lack of interoperability can be due to using different sources of ontologies on the Net, like DBpedia versus Wikidata. Also, as ontologies grow in size and become excessively detailed, it can become extremely difficult to establish correspondences (mappings) between two ontologies. Finally, they can present cultural and linguistic problems, given that multilingual and cross-cultural ontologies can find difficulties in overcoming cultural differences.

In the Semantic Web, ontologies facilitate machine-readable data integration by defining concepts, properties, and relationships using standardized languages like the Web Ontology Language (OWL) [2]. However, the diversity of ontological designs – ranging from general-purpose domain ontologies to specialized ones – introduces challenges in alignment, scalability, and adaptability **[3]**. For instance, in healthcare, a general ontology might classify "hypertension" under "cardiovascular diseases", but specialized extensions could incorporate patient-specific factors (e.g., comorbidities, medication interactions) for precise decision-making [4].

Interoperability issues arise from:

- Heterogeneity in Ontological Languages: Differing expressivity levels (e.g., OWL Lite vs OWL Full) or foundational top-level ontologies (e.g., DOLCE vs BFO) hinder alignment [5].
- Cultural and Linguistic Barriers: Multilingual ontologies struggle with contextual nuances [6].
- Scalability vs Precision: Large ontologies face alignment complexity due to excessive granularity [7].

To address rigidity in general ontologies, specialized variants adapt to domain-specific needs:

- Contextual Ontologies: Integrate situational factors (e.g., user preferences, time) for dynamic systems.
- Fuzzy Ontologies: Model vagueness (e.g., "tall person" with degree-based membership) [8, 9].
- Spatio-Temporal Ontologies: Combine spatial and temporal dimensions for applications like GIS [10].
- Probabilistic Ontologies: Handle uncertainty (e.g., inferring "cooking" with

80% confidence from sensor data) [11].

As for alignment techniques, they mitigate interoperability gaps by mapping entities across ontologies. Methods include:

- Lexical Matching: Comparing labels or synonyms [12].
- Structural Alignment: Analyzing hierarchical relationships.
- Machine Learning: Using embeddings (e.g., BERT) or neural networks.

Tools like LogMap and Alignment API (AML) automate alignment but face challenges in instance-level (A-Box) matching due to data heterogeneity.

While general ontologies provide broad coverage, specialized ontologies improve alignment precision in niche domains (e.g., healthcare or geospatial systems [13]). However, their diversity raises questions about scalability and cross-domain integration, which this survey explores.

In this paper, we dive into ontologies with a particular focus on specialized or context-dependent ontologies as well as ontologies' alignment, as these two are respectively crucial for adaptability and interoperability. This paper is organized as follows: Section 2 presents background information. Section 3 highlights the methodology that we followed to conduct this survey. Section 4 points out the findings, discusses the commonalities and differences among surveyed material, and emphasizes areas where research is lacking. Finally, Section 5 gives a conclusion.

2. Background

2.1. Specialized ontologies

Specialized ontologies are adapted to specific applications in order to meet the distinct requirements of particular fields [14]. They focus on yielding relevant terms and relationships that increase the utility of the ontology in its intended use case. Specialized ontologies include:

- Contextual ontologies: Contextual ontologies are designed to integrate contextual information that influences how concepts are understood within specific environments. By incorporating elements such as user preferences, situational factors, and temporal aspects, these ontologies enhance the relevance and applicability of knowledge representations in dynamic settings [15] and ensure that information remains pertinent and accurately interpreted.

Due to the variety (i.e., the diversity of data sources and formats that may not fit into rigid categories) of data, especially with the rise of Big Data, Contextual Description Logics (Contextual DL) [16] was introduced to manage different aspects of data quality within specific domains. In other words, it allows handling variations in data based on contextual changes. Thus, it adapts to contextual nuances that affect data quality.

Authors in [17] enable context reasoning to ensure, on the one hand, (i) interoperability between pervasive communicating devices by dividing the ontology into a shared general upper context and sub-domains' contexts, and on the other hand (ii) adaptability to inconsistencies when the user switches contexts rapidly, causing conflicts in sensor data. This second mitigation is achieved using "owl: ClassifiedAs" that can be either *deduced*, *aggregated*, *defined*, or *sensed* to consider the degree of trust in each type of context. They also consider the quality of context, among other things, to see how fresh the data is and consider it or not depending on this.

- Fuzzy ontologies: Fuzzy ontologies extend traditional ontological frameworks by integrating fuzzy logic [18] to manage uncertainty and vagueness in knowledge representation. This allows for the modeling of concepts that do not have strictly defined boundaries, facilitating more flexible reasoning in domains where precision is challenging [9]. In fact, the veracity (i.e., the degree of trust in sources) of data led to the use of Fuzzy Description Logics (Fuzzy DL) [19] to manage different aspects of data variability within specific domains. In other words, it provides variable membership, i.e., letting entities belong to many classes with variable degrees of membership. For instance, Fuzzy DL allows creating fuzzy concepts like *tall_person* and assigns a degree of membership to instances that belong to it. Thus, leaving a room for uncertainty.

In [20], authors show that fuzzy ontologies have better precision compared to crisp ontologies when it comes to Intelligent Transportation Systems, since the degree of opinion's polarity [21] from social media is taken into consideration in classifying cities and roads for travelers. As for the transport office, rule-based decision-making (thanks to real-time fuzzy data) is offered to determine congestion reasons and act accordingly. Nevertheless, Fuzzy DL is not included in Protege, for example, because these two are not standards of the Semantic Web. So, a plugin like "FuzzyDL plugin" needs to be installed.

- Probabilistic ontologies: They are frameworks that integrate ontological structures with probabilistic reasoning, enabling the representation and management of uncertainty in knowledge systems [22]. This allows for more robust inference and decision-making in scenarios with incomplete or ambiguous information.

Authors in [23]offer a probabilistic ontology for Human Activity Recognition (HAR) given the probabilistic nature of real-world axioms. High-level activities (inferred soft axioms, e.g., relaxing, cooking, etc.) are inferred using low-level activities (soft axioms that are derived from sensor data, e.g., person sitting in the kitchen, person's hands are on utensils, etc.) as well as defined assertion axioms, e.g., if a person is in the kitchen and his hands are on utensils then the odds of him cooking are 0.8.

The authors in [23] Hybrid approaches that integrate semantic similarity with probabilistic or statistical methods have shown significant improvements in focused web crawling by addressing limitations of purely lexical or ontology-based techniques. This underscores the value of combining semantic web technologies with conventional models to enhance the relevance and precision of retrieved information.

- Multimodal ontologies [24]: They are structured frameworks that integrate multiple types of data representations (such as text, images, audio, and video) into a cohesive ontology. These ontologies go beyond representing multimedia documents; they use **multiple modalities to define or illustrate concepts**. For instance, the concept **table** can be described through a **textual definition** ("a piece of furniture…"), a **formal OWL class**, and **images** of different types of tables. Some ontologies may also link to **videos** showing usage or **audio** describing assembly. This multimodal representation allows better understanding and reasoning, especially in areas such as translanguaging and sentiment analysis, where meaning is shaped by combinations of text, images, and sound. The rapid growth of Internet-enabled applications, such as social media platforms, e-commerce sites, and blogs, has led to a surge in user-generated content. This vast amount of data has made sentiment analysis increasingly valuable. Modern Aspect-Based Sentiment Analysis (ABSA) offers a more detailed approach by identifying sentiment trends related to specific aspects within the text. However, the challenge lies in analyzing reviews that are often short, unstructured, and filled with slang and emotive language, making it difficult to gauge customer opinions accurately. To address these issues, authors in [21] proposed an effective hybrid approach, "RoBERTa-1D-CNN-BiLSTM" for ABSA. Initially, the pre-trained Robustly optimized BERT approach (RoBERTa) and One-Dimensional Convolutional Neural Network (1D-CNN) models are used to extract features at the aspect level from the context of the review, following which classification is performed using Bidirectional Long Short-Term Memory (BiLSTM). The approach is evaluated on three cross-domain standards datasets, yielding an accuracy of 92.33%. The results of the experiments show that it surpasses the current leading methods in sentiment analysis and product recommendation. This integration enables comprehensive knowledge representation, facilitating enhanced understanding and reasoning across different modalities.

Authors in [25] emphasize the role of multimodal ontologies in separating speech from text in translanguiging (i.e., using many languages, dialects, and ways of communication to express themselves) as these two have varying meaning patterns, e.g., combining text with emojis to express emotion. They also emphasize both structural aspects of meaning (e.g., the size and placement of text in an image) and functional adjacencies between different forms of expression, e.g., combining both speech and images.

- Spatial ontologies: They are formal representations that define the concepts and relationships related to spatial entities and their properties. They provide a framework for understanding and modeling spatial information in different domains, like geography, urban planning, and environmental science.

Authors in [26] call for the enhancement of implementation and sharing of geospatial information to benefit Geospatial Information Systems (GIS). For this end, the ontology has to be logically sound, extensible, and implementable. They also address computational limits of spatial ontologies due to big geospatial data.

- Hybrid ontologies.
- Spatio-temporal ontologies: In [27], authors suggest a hybrid spatio-temporal ontology to offer a knowledge-aware tool that displays interactive maps using data from different ontologies like Geonames, where places' names are associated with URIs. In this application, icons appear and disappear based on the selected time.
- Temporal-events ontologies: In [28], authors represent time-oriented medical events through a hybrid Temporal Event Ontology (TEO) combining event-based ontologies and temporal ones. They introduce classes and properties to capture durations, e.g., *hasDuration*, specific time points, as well as recurring intervals. They provide two scenarios: the first one is when the start and end times for events are both known. The second is when only one time point is available for each event.

- Multimodal (holistic) and temporal-events ontologies: In [29], authors use temporal constraints (e.g., "*duration*": *for 40 minutes)* and identify co-occurring activities through "*while*", for example. They also emphasize the narration of activities that differ across modalities, e.g., "*combine*" versus "*add*", as well as the use of numbered lists in textual recipes versus conjunction adverbs like "*next*" and "*finally*" in audio ones.

2.2. Ontology alignment

In order to achieve interoperability between users or systems, many approaches have been provided in the literature. For example, authors allow interoperability between stakeholders or between Data Warehouse/Business Intelligence (DW/BI) systems and other Decision Support Systems (DSS) [30] either by defining core concepts for data warehousing in an ontology [31] or by aligning ontologies in the early stages of BI to eliminate heterogeneity [32, 33]. Also, in case users wanted to uncover relations within a DW through reasoner's inference [34], they opted for an added interoperability layer for mappings with an ontology.

In [35] authors suggested an instance-level alignment framework that used fuzzy logic; as existing research papers tend to focus more on aligning concepts Terminological Box(T-Box) since it is easier. They evaluated their ontology alignment system using the well-known benchmark: Ontology Alignment Evaluation Initiative (OAEI) [36] and compared their results to other systems' results that used the same benchmark. In fact, OAEI benchmark datasets contain pairs of ontologies that need to be aligned along with reference alignments (ground truth).

LogMap is another extensively utilized tool for ontology alignment, as noted by [37, 38]. It facilitates the matching of two concepts, such as 'person' and 'individual', from distinct ontologies by leveraging the lexical similarities of their labels. To achieve this, LogMap constructs a lexical index for each ontology. The research was further developed by [39], who first sought disjoint classes to prevent erroneous mappings. Secondly, they employed a similarity and dissimilarity comparison model known as the Siamese Neural Network (SiamNN), which is trained on paths between class pairs to learn relationships and predict mappings. Lastly, they utilized Hermit to validate the mappings based on subsumers.

In contrast, Alignment API (AML) [40] allows its users to choose from various alignment algorithms and combine them as needed. It supports linguistic-based algorithms, structure-based ones, as well as logic-based algorithms.

Whereas in [41], the authors illuminate the significance of user knowledge in improving the quality of alignments. In their proposed iterative system, users are initially requested to submit a partial alignment, which the system subsequently examines to eliminate candidate mappings that contradict the user's input. This approach effectively reduces the search space by incorporating user feedback.

In [42], the authors integrated ontologies to identify mappings. Although this step is typically not required, it may assist in establishing mappings when the ontology structures are difficult to ascertain. In reality, they employed hierarchical similarities to uncover these mappings.

In [43], the authors aligned ontologies using Bidirectional Encoder Representations from Transformers (BERT) for word embeddings. Consequently, entities were represented as vectors, and cosine distance was used to calculate their similarity.

In [44], although not necessarily using Wikidata for ontology alignment, they relied on it to improve both the quality and quantity of linkable data.

2.3. Specialized ontologies in alignment

In related work, many studies opt for certain kinds of specialized ontologies to align ontologies easily.

- Fuzzy ontologies: Authors in [45] used a framework that integrates fuzzy ontologies to improve interoperability among healthcare systems.
- Event ontologies: In [46], authors used event ontologies to facilitate alignment between different representations of events, particularly those from FrameNet and Wikidata. For this end, they considered superclasses and subclasses between events along with related events to foster precision when dealing with independent event ontologies.
- Multimodal ontologies: In [47], authors compared data across modalities since an image might yield visual clues that help refine the alignment of concepts that are ambiguous in text form.
- Contextual ontologies: Authors in [43] demonstrated the ability of contextual ontologies to improve mappings between large and complex ontologies. As a result, their BertMAP leveraged BERT's pretrained models and predicted synonym matches to map labels from different ontologies.
- Spatial ontologies: In [48] authors focused on wetland classification systems' alignment. In order to align similar concepts under different hierarchies, they considered proximity and area, amongst other things, to map key concepts in each ontology.

3. Methodology

Some of the challenges that we encountered while carrying out this survey are: the struggle that we had to find papers related to explanatory ontologies that are useful in domains where understanding how and why certain relationships exist is the main focus. One domain that can benefit from them is biology. In fact, explanatory ontologies are specialized ontologies that capture entities and the causal or explanatory relationships between them, such as why certain genes regulate specific biological processes. We also question, given the variety of domains, the number of specialized ontologies that exist or will exist in the future.

Another difficulty we had was filtering out papers that mistake thesauri for ontologies.

As for alignment ease based on ontology type, we believe the rank (from easiest to hardest to rank) is as follows:

1. Fuzzy ontologies, while simpler to align than rigid ontologies, may introduce complications in contexts where precision is essential.

2. Contextual ontologies lack a straightforward mapping process due to their dependence on a particular context of use. They can, however, assist in the disambiguation of terms in various systems, which can facilitate alignment in specific systems, particularly when contextual boundaries are clearly defined.

3. Spatial ontologies are moderately challenging to align, particularly in systems with varying spatial frameworks or scales. For example, when the ontologies that we wish to align define spatial boundaries, locations, and distances differently.

4. Multimodal ontologies are particularly challenging to align due to the disparities in data representations and the necessity of harmonizing information across models.

5. The synchronization requirement between various time representations and the requirement to ensure that event sequences are consistent across systems make temporal-event ontologies more challenging to align. It is also more difficult to align in real time.

6. Spatial-temporal ontologies are more complex than pure temporal or spatial ontologies due to the synchronization of both space and time.

7. Because of the integration of uncertainty and probability, probabilistic ontologies are difficult to align. Furthermore, the spectrum of probabilistic reasoning is highly variable across various domains.

To pinpoint relevant literature for our survey, a search strategy was defined, including search strings' definition, inclusion criteria, and search engine determination. Furthermore, the following Research Questions (RQ) were used for guidance.

RQ1: Are domain ontologies enough and ready to incorporate, or will further extensions be required based on the application where we want to use them?

This question seeks to determine studies that incorporate ontologies in their systems to see what kind of ontologies they opt for in order to cover aspects within their applications or domains.

RQ2: How do literature studies mitigate the variety of domain ontologies? This research question looks to uncover the different alignment methods that users follow to ensure interoperability.

RQ3: Are some specialized ontologies easier to align than others? This research question aims at: (i) checking if studies opt for specialized ontologies to ensure better alignment, and (ii) finding the level of difficulty or ease that every specialized ontology can bring.

As for research strings, two groups of keywords were used to conduct this survey:

- Group 1 includes keywords related to RQ1 and aims to get insight into the adaptability of ontologies to different use cases (domains or applications). The following keywords were searched in the titles: "ontology", "knowledge representation", "ontology-driven", and "context ontology". As the research progressed and we gained insight on the existence of specialized ontologies for every domain, the following keywords were added to the initial ones: "contextual ontology", "context-aware system ontology", "hybrid ontology", "fuzzy ontology", "temporal data ontology", "time-aware ontology", "spatio-temporal ontology", “temporal-event ontology”, “probabilistic ontology”, “multimodal ontology”, “holistic ontology”, “translingual ontology”, and “dynamic ontology”. Other refinement strings were used, particularly, “explanatory ontology”, which is sometimes referred to as “explanation ontology”. But since they barely retrieved a research paper, they were excluded. They are mentioned, though, in the findings and the discussion sections.

- Group 2 includes keywords for the retrieval of ontology alignment methods: “ontology alignment”, “mapping ontology”, “ontology matching”, and “ontology interoperability”.
- Group 3 combines keywords from Groups 1 and 2.

In regard to search engines, we mainly used Google Scholar as well as PubMed, given that the latter gives statistics on research papers per year. In the case of PubMed, we filtered the results only on the basis of English papers and did not restrict the year range to get statistics on how certain search queries evolved up to December 2023.

4. Result

4.1. Result

Figs 1-4 show statistics on the use of different types of ontologies over the years.

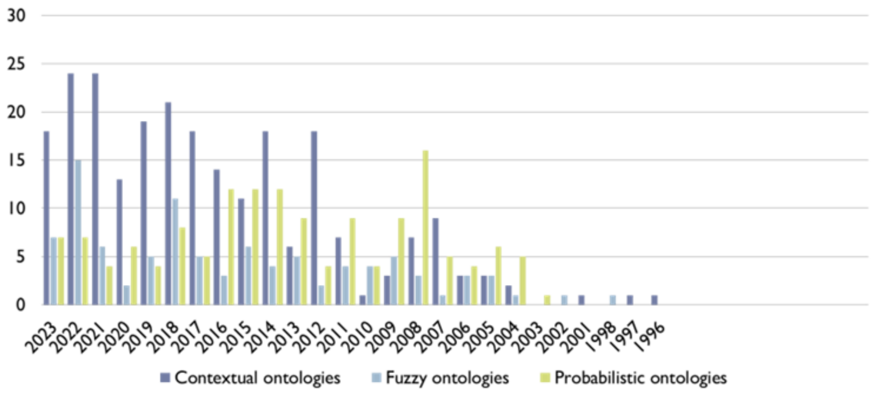

Fig. 1. PubMed timeline results by year for three different search queries

Fig. 1 shows that the search query “contextual ontologies” retrieved the highest number of papers in PubMed as opposed to fuzzy and probabilistic ones. Moreover, in 2021 and 2022, 24 papers used contextual ontologies reflecting growing interest in context-aware systems and Internet of Things (IoT) applications. Probabilistic ontologies attained their peak in 2008 with 16 search results, but their use has been decreasing since then, likely due to the rise of alternative uncertainty-handling methods such as fuzzy logic and probabilistic models embedded directly into algorithms. Similarly, fuzzy ontologies made more time to peak in 2022 with 22 results, suggesting increasing importance in handling vagueness and subjectivity, particularly in domains like sentiment analysis and natural language processing.

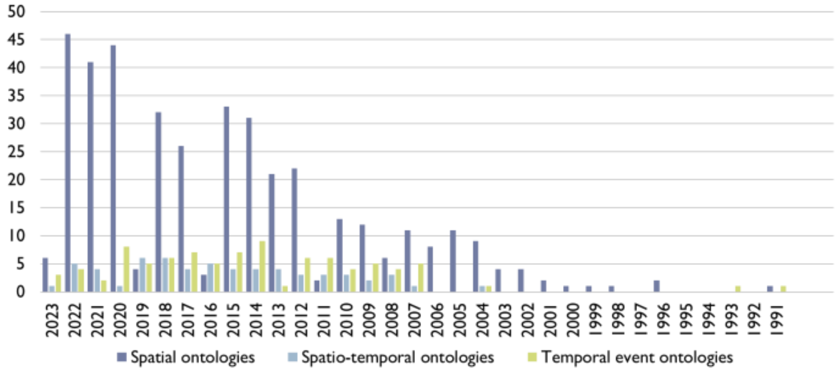

Fig. 2. PubMed timeline results by year for three different search queries

From Fig. 2, we notice that spatial ontologies are the most used in literature compared to spatio-temporal or temporal-event ones. The peak of spatial ontologies, which occurred in 2022 with over 45 publications, reflects the strong role of spatial representation in biomedicine. In contrast, spatio-temporal ontologies and temporal-event ontologies remain relatively scarce, rarely approaching 10 publications per year. This limited uptake may be due to the higher modeling complexity of representing both space and time simultaneously, as well as the fact that many temporal aspects are often handled directly by databases or event-driven systems rather than ontologies.

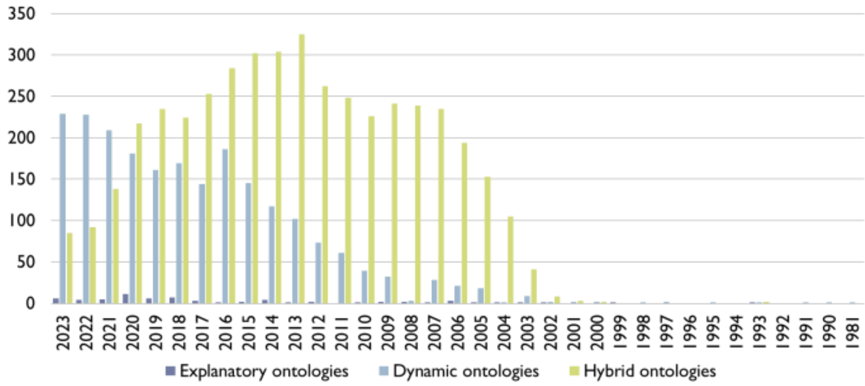

Fig. 3. PubMed timeline results by year for three different search queries

According to Fig. 3, hybrid ontologies had a peak of 325 in 2013 but have been decreasing since then. Their decline after 2013 likely reflects the growing use of machine learning and knowledge graph embeddings, which offer alternative ways to achieve hybrid reasoning without explicitly labeling work under "hybrid ontologies". In contrast, "dynamic ontologies" and "explanatory ontologies" appear more modest in number but show a steady presence, suggesting ongoing but more niche research communities.

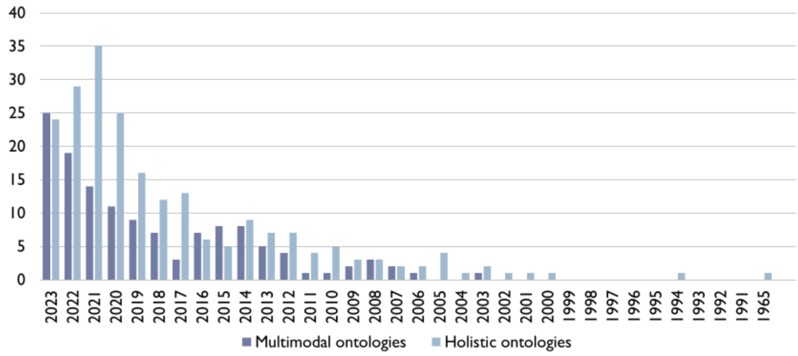

Fig. 4. PubMed timeline results by year for two different search queries

From Fig. 4, we can see that multimodal ontologies are still increasing in use compared to holistic ones that peaked in 2021 with 35 results, but have started decreasing since then. The rise of multimodal ontologies reflects the growing importance of integrating heterogeneous data sources such as text, images, genomic sequences, and clinical records for biomedical research and Artificial Intelligence (AI) applications. In contrast, holistic ontologies, which aim to provide comprehensive unified frameworks, may have declined due to their complexity and the shift toward modular, application-driven ontology development.

Fig. 5 shows the number of papers that used "ontology mapping" per year.

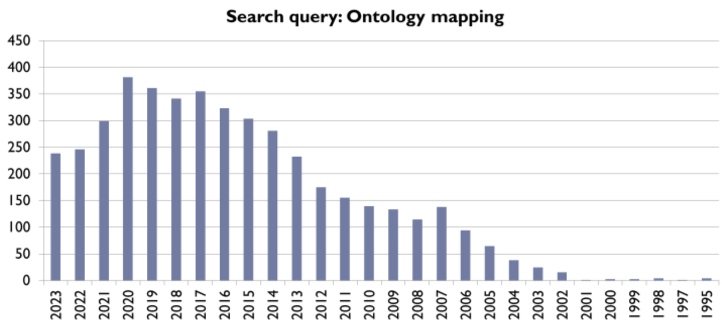

Fig. 5. PubMed timeline results by year for "ontology mapping" search query

Fig. 5 indicates that "ontology mapping" articles have been increasing in PubMed up until 2020, with 381 papers. But they started falling since then. Nevertheless, they are still very commonly used, with 238 papers in 2023. A plausible explanation for the decline in **ontology mapping** publications after 2020 is the methodological and terminological shift in the field. Recent alignment approaches increasingly rely on word embeddings, transformer models (e.g., BERT, BioBERT), and graph embeddings, and are often described under alternative terms such as **semantic matching**, **entity linking**, or **knowledge graph integration**. For instance, authors in [49] tailor knowledge graph embeddings for ontology alignment rather than using classical string or structural matching, while other recent work [50] highlights the role of Large Language Models (LLMs) in accelerating ontology modeling, extension, and alignment. Consequently, the apparent decrease in PubMed counts likely reflects this evolution in methods and terminology rather than a genuine decline in research activity.

4.2. Comparison and analysis

We noticed from existing literature that using spatial ontologies has the potential to extend Geonames, for example, so as to add zoning regulations, distances between locations, and define region boundaries, among other things. Thus, leveraging the capabilities of domain ontologies and adapting them to our needs. We reckon that the peak in spatial ontologies with 46 results in 2022 (Fig. 2) and their constant increase in use could be related to their high applicability in many domains, such as location-based systems and applications evolving maps, as well as geospatial technologies. Nevertheless, in 2023, the number of papers associated with spatial ontologies dropped drastically in PubMed. This sudden decrease could be explained by a shift in academic focus. But, this theory may be proven right or wrong in the next year if the number of papers keeps decreasing. As for contextual ontologies, they are mainly used in domains like Ambient Intelligence to adapt to people's presence and pervasive computing or context-aware systems, where adapting to context is of need. Consequently, we believe that the peak in research (Fig. 1) for contextual ontologies during the last couple of years could be influenced by their applicability across various domains, especially the IoT, which has been gaining more interest recently. And although both fuzzy and probabilistic ontologies are used in uncertain scenarios, probabilistic ones rely on quantitative values, e.g., 0.8, whereas fuzzy ones use linguistic terms like "very likely" due to vagueness in Natural Language Processing (NLP). Thus, the recent peak in the usage of fuzzy ontologies could be attributed to the increased interest in capturing nuanced sentiments in social media. On the contrary, probabilistic ontologies have decreased in use (Fig. 1) because not only do they not handle uncertainty, which is a main concern in Big Data, but they are also already embedded in algorithms using probabilistic models. And when it comes to temporal ontologies, they are well-suited to applications involving planning or scheduling. Hence, they tend to be combined with other specialized ontologies to create a hybrid one. However, one way to explain the decrease in use of hybrid ontologies (Fig. 3) is perhaps linked to the use of specific hybrid ontology names as opposed to using a generic word like hybrid. Another way of explaining that decrease could be that hybrid ontologies are more challenging, and other techniques are preferred to combining multiple ontologies. On the contrary, dynamic ontologies are still increasing in use with 229 results in 2023 (Fig. 3); as these ontologies have very high applicability across domains that evolve, like changing market dynamics, drug interactions, climate change, supply chain management, etc. On the contrary, explanatory ontologies have very low usage numbers. One reason for that is the low need for these ontologies. As for multimodal ontologies, they are of paramount importance. In fact, they make distinctions between individual modes of human-computer interactions. Each mode has its own specificities, and separate representations are crucial for understanding. On the contrary, holistic ontologies focus rather on the shared characteristics and the interrelations between components. In other words, the system is seen as a whole without isolation between its elements.

Concerning ontology alignment and based on related work, the choice between T-Box versus A-Box alignment is sometimes difficult, especially since each of these two types of alignment comes with varying opportunities, and A-Box alignment is harder. While T-Box alignment ensures a shared understanding [17, 31] and data enrichment [51] using a common vocabulary, A-Box alignment is used when dealing with heterogeneous data where individuals are the main focus. It is considered harder because instances come in (i) varying formats and can be (ii) described at different levels of granularity, which makes them harder to find. Furthermore, as the number of instances increases, scalability issues will rise. Also, instances are associated with (iii) uncertainty since they may be incomplete. Hence, authors in [35] chose fuzzy logic for their alignment. Additionally, instances are more (vi) dynamic and constantly changing. Last but not least, they can be presented using a highly (v) expressive profile. In that case, one has to deal with complex rules to get to them. As for statistics regarding ontology mapping (Fig. 5), they are high because they are applicable and crucial in any domain and for all types of ontologies. Furthermore, many specialized ontologies have been used for aligning ontologies with more ease. Some are versatile, like fuzzy ontologies (for vague concepts, e.g., wealth), contextual ontologies (when meaning depends on surrounding data), probabilistic ontologies (when concepts are not universally agreed upon or when ontologies have varying levels of detail), multimodal ontologies. Whereas others are specific to certain needs like temporal ontologies, event-based ontologies, and spatial ones. We believe that these ontologies could be combined based on applications' needs for better alignment.

4.3. Discussion

Although general-purpose ontologies (i.e., domain ontologies) are expressive, they are rigid, and further extension is required to adapt them to specific characteristics or aspects of each application. For this end, studies from literature chose to tailor them into contextual, fuzzy, spatial, etc., to respond to certain criteria within their applications.

The good news, though, is that specialized ontologies foster interoperability in sharing a common understanding across a specific domain. And we noticed that most studies from the literature are well aware of its paramount importance and tend to find different ways to ensure it: either they define core concepts [31] or upper concepts [17], or they align ontologies [33]. Another option that has a lot of perks but is less used, regardless, is Wikidata, which offers matchings with other ontologies. With that being said, the expressiveness of (specialized) ontologies and their scalability can either lead to mapping issues or ease them.

Three considerations should guide the choice of approach when designing or adapting ontologies:

1. Characteristics of the domain

- Domains with **high contextual variability** (e.g., IoT, clinical decision support) benefit from contextual ontologies.
- Domains with **intrinsic uncertainty or vagueness** (e.g., patient symptoms, social science concepts) may require fuzzy or probabilistic ontologies.

- Domains where **space and time are essential** (e.g., epidemiology, environmental monitoring) should extend domain ontologies with spatial and temporal modules.

2. **Availability of resources** (ontologies, thesauri, documents, databases).

- If only a thesaurus/a relational database/unstructured documents exist, **they can be transformed into a domain ontology** through ontology learning [52].
- If multiple overlapping ontologies exist, ontology alignment and integration techniques **should be prioritized**.
- If open knowledge graphs (e.g., Wikidata, DBpedia) are available, **they can be used for bootstrapping or linking** to external ontologies.

3. **Goals to achieve**

- If the goal is **interoperability across systems**, aligning or mapping ontologies is essential.
- If the goal is **explainability**, adopting **explanatory ontologies** that capture causal relations is preferable.
- If the goal is **scalability and automation**, lightweight ontologies supported by embeddings or LLMs may be more practical.
- If the goal is **multimodal integration** (e.g., images, text, genomic data), **multimodal ontologies** are the most suitable.

4.4. Future directions

In the future, we consider looking for other search strings to cover a broader range of specialized ontologies, like security ontologies for cybersecurity knowledge representation, dynamic ontologies for domains that evolve, and social ontologies for social networks.

Additionally, since reasoners for traditional ontologies are generally not suited for specialized ones and are not built to handle the uncertainty of fuzzy logic or time intervals, among other things, nor are traditional benchmarks, we consider exploring specialized benchmarks for specialized reasoners.

Also, we consider finding ways to lessen the challenges related to using specialized ontologies to improve alignment. For instance, when only a domain ontology is available, integration with other domain ontologies can be challenging because of the differences in scope (e.g., a cardiology ontology focusing on heart diseases vs a broader medical ontology covering all diseases), granularity (e.g., one ontology representing “Cancer” as a single class while another distinguishes “Lung Cancer”, “Breast Cancer”, etc.), and formalism (e.g., an ontology modeled in OWL DL vs a thesaurus-like taxonomy without reasoning support). A practical way forward is to extend the domain ontology with specialized ontologies according to integration needs: Contextual ontologies can adapt concepts to dynamic environments, e.g., in smart homes where “light” means sunlight in one context and a lamp in another, as contextual ontologies are useful in pervasive computing. Another example of their usefulness in a smart home would be the concept *“temperature”*; it can mean *air temperature* in one context and *water temperature* in another. These are context dimensions that can be added to improve adaptability and ease alignment. When it comes to temporal ontologies, they can be used in the case of a clinical ontology, for example, that defines treatment as a medical procedure in order to add temporal properties like has_start_date, has_duration, and recurs_every. These properties would allow scheduling and make alignment easier when two domain ontologies are using one class versus many classes to refer to a treatment. In case only a thesaurus is available, we need to change it into an ontology. This is called ontology learning and allows generating an ontology from a relational database, a thesaurus, a text, etc., and is based on many rules that we can dig deeper into in future work.

5. Conclusion

To conclude, we can say that ontologies have been extended to accommodate specific aspects within domains. Also, with specialized ontologies comes the necessity of specialized reasoners and benchmarks. Furthermore, it is safe to say that expressiveness affects interoperability and vice versa, both in a good and a bad way, and opting for specialized ontologies has the potential to solve interoperability problems across the domain in question. These specialized ontologies are more valuable and go up and down in usage based on shifts in research trends and applicability. Furthermore, specialized ontologies can be combined when dealing with more generic ontologies for improved alignment. But we need to be cautious, as some of these specialized ontologies come with challenges.

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