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Encontros Bibli

CLARIFYING AND CONSOLIDATING GRAPH-BASED KNOWLEDGE REPRESENTATIONS IN LIS: A TERMINOLOGICAL FRAMEWORK

Esclarecendo e consolidando representações de conhecimento baseadas em grafos na Biblioteconomia e Ciência da Informação: um quadro terminológico

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RESUMO

Objetivo: o presente estudo tem como propósito consolidar termos-chave relacionados à representação do conhecimento baseada em grafos, como grafos de conhecimento, rede semântica, grafo semântico e ontologia, examinando como são definidos e utilizados na literatura científica.
Método: realizou-se uma revisão sistemática da literatura, recuperando 474 estudos publicados entre 2019 e 2023 em repositórios científicos de destaque, dos quais 288 atenderam aos critérios de inclusão e foram analisados.
Resultado: a análise revela uma sobreposição substancial na conceituação dos termos de representação baseada em grafos, ao mesmo tempo em que expõe nuances importantes. As ontologias permanecem como fundamento na área de Ciência da Informação, sendo frequentemente associadas à modelagem de domínio e à integração semântica. Em contraste, os grafos de conhecimento apresentaram rápido crescimento nos últimos anos, especialmente em contextos aplicados envolvendo inteligência artificial e fusão de dados. Outros termos, como redes semânticas e grafos semânticos, são utilizados de forma menos consistente e frequentemente carecem de definições formais, indicando fragmentação no uso da terminologia.
Conclusões: este estudo avança na compreensão teórica das representações de conhecimento baseadas em grafos ao esclarecer limites e intersecções terminológicas. Ele oferece um quadro consolidado que apoia o alinhamento conceitual entre disciplinas, promovendo um uso mais coerente em pesquisas e aplicações futuras.
PALAVRAS-CHAVE: Grafo de conhecimento. Grafo de causalidade. Rede semântica. Ontologia.

ABSTRACT

Objective: the present study aims to consolidate key terms related to graph-based knowledge representation, such as knowledge graph, semantic network, semantic graph and ontology, by examining how they are defined and used in scientific literature.
Methods: a systematic literature review was conducted, retrieving 474 studies published between 2019 and 2023 from major scientific repositories, of which 288 met the inclusion criteria and were analyzed.
Results: the analysis reveals substantial overlap in the conceptualization of graph-based representation terms while also exposing important nuances. Ontologies remain foundational within Library and Information Science, being often associated with domain modeling and semantic integration. In contrast, knowledge

graphs have experienced rapid growth in recent years, particularly in applied contexts involving artificial intelligence and data fusion. Other terms, such as semantic networks and semantic graphs, are used less consistently and often lack formal definitions, indicating fragmentation in terminology usage.
Conclusions: this study advances the theoretical understanding of graph-based knowledge representations by clarifying terminological boundaries and intersections. It offers a consolidated framework that supports conceptual alignment across disciplines, promoting more coherent usage in future research and applications.
KEYWORDS: Knowledge graph. Causality graph. Semantic network. Semantic graph. Ontology.

1 INTRODUCTION

Library and Information Science (LIS) uses Knowledge Organization Systems (KOS) to manage and structure knowledge originating from diverse sources. One of the key challenges in this endeavor is addressing linguistic ambiguity, in which different terms refer to the same underlying concept (Tudhope; Nielsen, 2006; Souza; Tudhope; Almeida, 2012). KOS plays an important role in resolving these ambiguities by formalizing relationships between concepts. Over time, they have evolved from simple controlled vocabularies and term lists to more complex structures, such as ontologies (Gonçalves; Tognoli, 2022; Zeng, 2008).

Among the various forms of KOS, ontologies are considered the most expressive, as they provide accurate modeling of real-world relationships and incorporate formal axioms to support logical inference (Lima; Maculan, 2017; Pontes; Lima, 2012). Ontologies make a conceptual distinction between universals, that being general categories, such as “human”, “butterfly” or “canine”, and particulars, which are individual instances of these categories (Smith, 2004; Guarino, 1998). This ontological distinction enhances the semantic structure of information systems and promotes greater interoperability between them.

The representation of particulars in computational systems has been a longstanding topic in the history of Knowledge Representation. Early works, such as those by Quillian (1967), explored how machines could represent and process knowledge about the world, while Bobrow and Winograd (1977) emphasized the role of natural language as an intermediary in machine reasoning. These foundations support the development of systems that apply Artificial Intelligence (AI) across various domains, task-specific, linguistic or common-sense, by leveraging formal representations for deduction and knowledge extraction.

In this context, graph-based representations have emerged as effective tools for modeling entities and their relationships. Semantic networks, pioneered by Simmons and Slocum (1972), and taxonomic hierarchies using the “IS-A” relation, as proposed by Brachman (1983), were foundational in enabling class-based inheritance in knowledge models. Since then, multiple overlapping terminologies, such as causality graphs, knowledge graphs (KG), semantic graphs, semantic networks and ontology, have emerged to describe similar or related representational structures.

Despite the increasing adoption of ontologies and graph-based models within KOS, the terminology used across the literature remains inconsistent, leading to conceptual ambiguity. This lack of terminological clarity underscores the need for a more systematic examination of the semantic distinctions and overlaps among these terms. Specifically, this study seeks to clarify how different graph-based representation terms are used within LIS, aiming to develop a consolidated framework that supports clearer semantic understanding and application.

To address the issue, the present study poses the following question: What are the similarities and differences in graph-based representations within Library and Information Science (LIS)? In order to answer this question, we conducted a Systematic Literature Review (SLR) focused on scientific publication related to graph-based knowledge representation in LIS. From an initial corpus of 474 studies, 288 met the inclusion criteria and were selected for detailed analysis.

Based on this review, we identified and categorized five main types of graph-based representations: (i) causality graphs; (ii) knowledge graphs; (iii) semantic graphs; (iv) semantic networks; and (v) ontologies. This categorization aims to clarify their conceptual boundaries among these forms of representation, offering a consolidated framework that enhances semantic understanding and informs their practical applications in knowledge organization.

2 BACKGROUND

This section explores the distinction between universals and particulars, a fundamental ontological dichotomy, relevant to KOS. In this context, universals refer to abstract “models”, or general categories, that structure knowledge, while particulars denote individual data instances that represent these “models”.

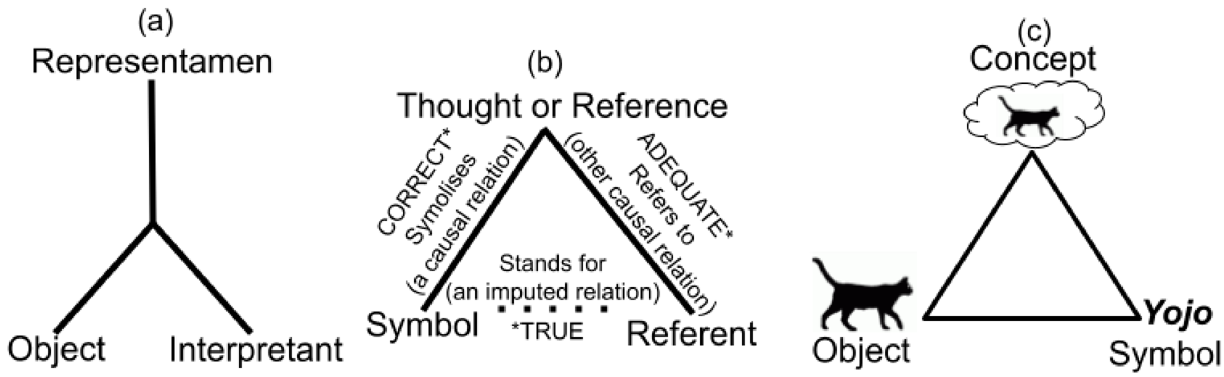
Gruber (1993, p. 199) defines an ontology as “an explicit specification of a conceptualization”. Building on this, Borst (1997, p. 23) emphasizes its collective dimension by describing ontology as “a formal specification of shared conceptualizations”. In other words, an ontology formally expresses a set of meanings that are commonly understood within a given domain. This shared understanding enables interoperability and consistent interpretation across systems.

In ontological modeling, concepts, often treated as classes, are understood in a broad sense. They may represent abstract or concrete entities, be elementary or composite in structure, and correspond to real or even hypothetical objects (Almeida, 2014; Smith, 2004). For instance, the terms “cat”, “chat” or “gato” represent the same mammal (a thing) in different natural languages (Section 2.2). Regardless of the linguistic variation, the referent, the concept entity, remains the same (Section 2.1). When a particular instance of that concept is given a name, such as “Tom”, for a specific individual, the referent becomes individualized (Section 2.3). This process of individuation is essential in knowledge representation, as it allows systems to distinguish between general knowledge structures and their specific manifestations in the world.

2. 1 SEMIOTIC CONSTRUCTION OF CONCEPTS

A concept can be understood as the integration of meaning, term and referent (Maculan; Lima, 2017). Dahlberg (1978) defines a *thing* as any entity that can be referred to (referent) and which is assigned a correct description (meaning) through a verbal form (term). Figure 1 illustrates three perspectives on the construction of concepts, based on foundational semiotic and cognitive models: Peirce's theory of signs; Ogden and Richards' triangle of meaning; and Sowa's framework of mental representation. Although each model adopts different terminologies and emphases, they converge in illustrating the triadic structure of conceptual representation. Specifically, Peirce’s model comprises the representamen, interpretant and object; Ogden and Richards propose the triad thought (reference), referent and symbol; and Sowa’s framework includes concept, symbol and object. Each of these models reflects a different theoretical lens on how concepts are cognitively constructed, linguistically expressed and semantically anchored in referents. Together, these models offer a robust foundation for understanding how meaning is mediated and represented in KOS.

Figure 1 - Semiotic representation of things in reality



Source: (a) Peirce (1932); (b) Ogden and Richards (1923); (c) Sowa (2000).

Peircean semiotics lays the foundation for the theory of signs by explaining how an interpreter assigns a name to an object (Peirce,1932). Although the theory does not depend directly on psychology or linguistics frameworks, it addresses the symbolic relationship between the psycholinguistic process and the object itself. As illustrated in Figure 1 (a), (i) the sign (or representamen) is the most inclusive representation; (ii) the object (semiotic object) is the entity to which the sign refers, its essence within a given context; and (iii) the Interpretant (or interpretant sign) is a mental effect or understanding produced by the act of interpretation. In turn, Ogden and Richards (1923) describe a model based on causal relations. According to their semantic triangle, there are causal links between symbol and thought and between thought and referent, but no direct connection between symbol and referent. In Figure 1 (b), this is clarified as follows: (i) thought is what correctly relates a thing to its symbol; (ii) thought invokes a word to refer to that symbol; and (iii) the referent, in grammatical terms, is what the symbol stands for.

Figure 1 (c), based on Sowa (2000), introduces a distinction between the object denoted by a word and its corresponding mental representation. For example, the image of a cat in a cloud represents the concept (mental representation) of a real-world object, a cat, named “Yojo” (symbol). This illustrates how mental, linguistic and real-world referents are interconnected in conceptual modeling.

In a broader context, real-world semantics refers to objects as they exist, independently of language or culture. Ontologies are designed to manage and refine the nuances of representation across the domains. By making such distinctions explicit, ontologies provide a more accurate and semantically rich representation of concepts (Gomes; Barros, 2019; Zeng, 2008).

2.2 ONTOLOGIES AND MODELS

Ontological concepts represent entities and phenomena from reality in a structured and meaningful way. According to Simperl and Tempich (2006, p. 836), ontologies are “regarded as a means for a shared knowledge understanding and a way to (formally) represent real-world domains”. In addition, Smith (2004, p. 76) states that ontologies are the manner of “understanding concepts effectively as tools [...] which we can use to gain cognitive access to corresponding entities in reality”. In this sense, ontologies serve as structured models that represent concepts and their relationships captured from reality. This process requires describing things with some language that can represent all of their features.

In ontological modeling, perceptions identify patterns through an ontological language, describing conceptualizations to create a model. The quality of an ontology depends on how effectively it represents the intended model. The vocabulary determines how expressive the ontology is; thus, some authors research foundational or upper ontologies.

Numerous authors provide vocabularies of their ontology to allow reusability of abstraction, which is essential for generalization. Upper ontologies achieve this with a joint base of definition universals (Dominguez Santana *et al*. 2024; Guarino; Welty, 2004; Guizzardi; Falbo; Guizzardi, 2008; Smith, 2004). To allow reuse, it is necessary to create a set of classes of universals that are common concepts, aided by a foundational ontology. When an instantiation of a class occurs, it is called particular or individual, which is discussed in the next section.

2.3 ONTOLOGICAL PARTICULARS AS INDIVIDUALS

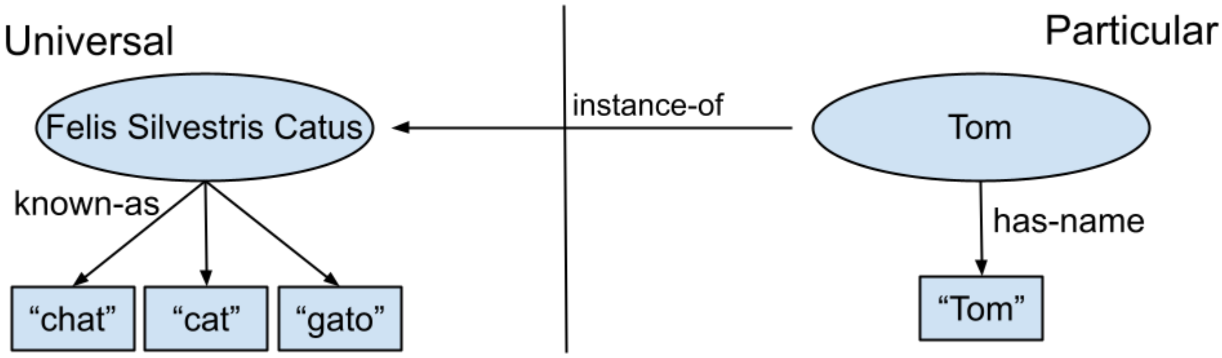
As discussed in the previous sections, the ontological modeling of a cat is an effort to represent and formally generalize a concept derived from reality. However, when we name particular cats "Tom" and "Kitty", these entities gain specific properties that allow us to identify them individually. Therefore, the literature refers to these entities as particulars or individuals.

Aristotle defines "universal" as something that naturally applies to multiple things, while a "particular" does not. For example, "man" is universal, while "Callias" is particular (Ackrill, 1963, p. 47). Besides, Lowe (2006) emphasizes the importance of instantiation, which defines all the properties universally applicable to an individual. In other words, a particular inherits all the properties associated with its universal but may possess additional properties not found in its parent.

According to our model, if Tom is categorized as a cat, then Tom possesses all the properties of a cat. However, Tom may also possess other properties that are not shared with other cats, such as “black”. This is because there are cats in the world that are not black. Therefore, Tom is an instance (particular) of a universal, inheriting all the relevant properties of the concept. However, a universal must be generic enough to abstract material features.

Figure 2 illustrates the instantiation process, where a universal concept (e.g., Felis Silvestris Catus) is represented by particular instances (e.g., Tom) with specific properties (e.g., name and color). Ellipsis represents a class (kind) of concept that can be universal or particular. A rectangle is a property that can have any value. An arrow represents a class to class or class to properties relation.

Figure 2 - Universal and particular properties



Source: prepared by the authors (2025).

This representation shows that there is an identifier Tom (particular), which is a name (has-name) “Tom” where it is an instance of Felis Silvestris Catus (Universal), known as (known-as) chat (French), cat (English) or gato (Portuguese).

When we have a set of particulars, it can be treated as a database (Duan *et al.*, 2017; Menon; Krdzavac; Kraft, 2019). Graph-based representation is relevant in cases where (i) each item has a complex representation, (ii) information is incomplete and incremental and (iii) needs an active role in deducing relationships (Borgida *et al.*, 1989). Hence, some authors use various terms to express a set of connected graphs to represent complex data.

Some terms are: (i) causality graph, which identifies the causal relations between causal concepts (Heindorf *et al.*, 2020; Zhang *et al.*, 2013); (ii) KG, which is a data model to capture, organize and represent knowledge for advanced application (Chen; Jia; Xiang, 2020; Hogan *et al.*, 2021); (iii) semantic graph, which elicits concepts and relationships (Yadav; Sharan; Joshi, 2014); and (iv) semantic network, which is used to express a connection to meaning between items (Jung; Lee, 2020; Shi *et al.*, 2017). The next section presents studies that have conducted literature reviews on these terms.

2.4 RELATED WORKS

Previous research on graph-based knowledge representation has tended to concentrate on specific formalisms or application domains rather than systematically comparing the underlying representational terms. Grandi *et al*. (2024), for example, conduct a systematic review of semantic networks derived from concept maps, supported by a specialized bibliometric process that characterizes how concepts and relations are modeled and analyzed in educational and informational contexts. Although the study refines the understanding of semantic networks as directed graphs whose nodes represent concepts and edges represent semantic relations, its scope is limited to a single representational type and does not address how semantic networks relate to other graph-based constructs such as KG or ontologies.

In parallel, research on causal KG has advanced the integration of causality and graph-based modeling, particularly in explainable AI and domain-specific reasoning. Jaimini and Sheth (2022) propose a framework that enriches KG with interventional and counterfactual reasoning capabilities to improve explainability, emphasizing hyper-relational representations of causal dependencies rather than terminological or conceptual comparison with other graph formalisms.

Xu and Ichise (2025) extend this line, which combines a causality KG with a domain ontology to represent financial expertise. Their approach demonstrates how causal relations and ontological structures can be integrated to support reasoning in a specialized domain, but it remains focused on financial applications and does not problematize the broader vocabulary of graph-based representations.

At a more general level, Ji *et al*. (2022) provide a comprehensive survey of KG, covering their representation, acquisition and applications, and proposing taxonomies for embedding models, completion methods and knowledge-aware tasks. While the survey consolidates definitions and perspectives on KG and situates them within the broader AI ecosystem, it largely treats the terminology surrounding KG as given and does not systematically contrast them with related constructs such as semantic networks, semantic graphs or ontologies across different disciplinary traditions.

In contrast to these contributions, the present study undertakes a SLR that explicitly targets the conceptual and terminological relationships among major graph-based representation terms; KG, causality graph, semantic network, semantic graph and ontology; across disciplines, with particular attention to LIS. By examining how these terms are defined, differentiated and sometimes used interchangeably, this work clarifies conceptual overlaps and distinctions and proposes an integrated analytical perspective that complements and extends prior reviews on individual formalisms or application areas. This consolidation supports a more coherent understanding of the variety of concepts and the extent to which they share semantic and structural similarities. The following section presents the methodological procedures adopted to address this problem.

3 METHOD

This section discusses the methodology used to analyze the similarities and differences between these graph-based representation terms. Kitchenham (2004) emphasizes that an SLR is a rigorous and auditable process, making it a fair and reliable method.

The Kitchenham (2004) approach is divided into three main phases: (i) planning, which involves defining the aim and protocol of the review; (ii) conducting, which includes identifying relevant research, selecting studies and assessing their quality; and (iii) reporting, which summarizes the gathered information.

3.1 PLANNING

The literature on graph-based representation exhibits a diverse terminology (Section 2.3). This study aims to examine the similarities and differences among these recurring terms. The research questions (RQs) are: (RQ1) Do authors refer to the same concept using different terms? (RQ2) What are the distinctions between these approaches?

Based on the RQs, the main terms for search are: (i) knowledge graph, (ii) causality graph, (iii) semantic network, (iv) semantic graph and (v) ontology. In addition, we seek some definition or conceptualization. In this context, there are other terms, such as (i) definition, (ii) concept and (iii) conceptualization. Table 1 shows the string used on scientific repositories in the title field.

Table 1 - Strings used on scientific repositories

Field	String
Title	("knowledge graph" OR "causality graph" OR "semantic network" OR "semantic graph" OR "ontolog*") AND (definition OR concept*)

Source: prepared by the authors (2025).

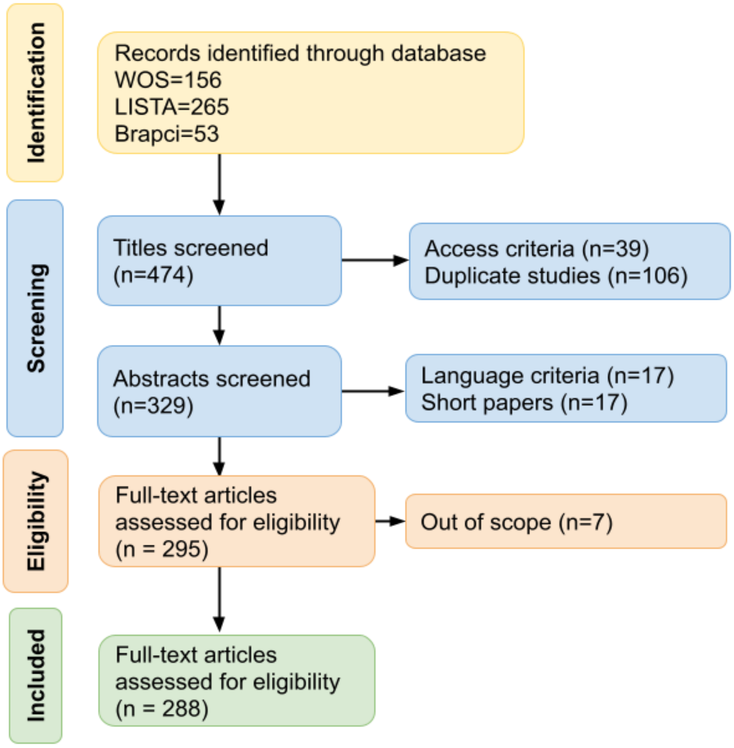
The criteria for selecting the scientific databases are as follows: (i) they must be open access or accessible through the Comunidade Acadêmica Federada (CAFe) and (ii) they must allow filtering for LIS publications. Several widely used scientific databases were initially considered but excluded because they do not provide specific filtering options for LIS or do so only in limited or inconsistent ways. Based on these requirements, the following databases were selected: (i) Web of Science (WOS); (ii) Library, Information Science and Technology Abstracts (LISTA); and (iii) *Base de Dados Referenciais de Artigos de Periódicos em Ciência da Informação* (Brapci).

The inclusion criteria are: (i) publications from 2019 to 2023; (ii) complete online access; and (iii) papers discussing knowledge graphs, causality graphs, semantic networks, semantic graphs or ontologies. The exclusion criteria, in addition to not meeting the inclusion criteria, include: (i) duplicate studies (only one will be used); (ii) short articles (fewer than 5 pages); (iii) not written in Portuguese, Spanish or English; and (iv) redundant works (the most complete version will be considered).

3.2 CONDUCTING THE REVIEW

The review process follows the planning outlined in Section 3.1, to ensure methodological rigor, the quality of the included studies was assessed during the full-text screening phase, following Kitchenham’s (2004) recommendations for systematic reviews. The evaluation considered completeness of methodological reporting, conceptual clarity, and relevance to the research questions. Potential risks of bias were also examined, including selection bias (e.g., access restrictions, language constraints), publication bias (e.g., predominance of peer-reviewed sources), and methodological bias within the studies themselves (e.g., insufficient detail in data collection or analysis). To mitigate these risks, predefined inclusion and exclusion criteria were applied consistently. Figure 3 depicts the systematic progression of the SLR through a rigorous, multi-stage screening and eligibility protocol consistent with PRISMA guidelines (Rethlefsen; Page, 2022). A total of 474 records were initially retrieved from three major databases; WOS (n = 156), LISTA (n = 265), and Brapci (n = 53). During the screening phase, title evaluation resulted in the exclusion of studies due to access restrictions (n = 39) and duplicate entries (n = 106), yielding 329 articles for abstract assessment. At this stage, additional records were removed for not meeting the language criteria (n = 17) or for being short papers lacking sufficient methodological detail (n = 17). Subsequently, 295 full-text articles were examined for eligibility, of which seven were excluded for being out of scope. Ultimately, 288 studies met all predefined inclusion criteria and were incorporated into the final synthesis.

Figure 3 - PRISMA flow diagram to show the inclusion-extraction process



Source: prepared by the authors based on the study's data (2025).

3.3 QUALITATIVE ANALYSIS OF THE SELECTED STUDIES

After the selection process, the 288 studies were subjected to a qualitative analysis based on content analysis procedures, following Kitchenham's (2004) recommendations for systematic reviews. The goal of this phase was to identify how each graph-based representation term (KG, causality graph, semantic network, semantic graph and ontology) is defined, described or conceptually distinguished in the literature.

The analysis was carried out in three stages: (i) Pre-analysis: All articles were read in full, and segments related to the definitions, conceptualizations or descriptions of the target terms were extracted. A data extraction form was created to ensure consistency, including: bibliographic information, term(s) addressed, explicit definition (if any), structural properties mentioned, purpose of use and methodological notes.

(ii) Coding and categorization: Using qualitative coding, each extracted segment was coded according to analytical categories defined through a hybrid strategy; partly derived from the literature and partly refined inductively during familiarization with the corpus. The final coding scheme contained the following categories as shown in Table 2.

Table 2 - Qualitative analysis categories

Category	Definition
Definition	presence, clarity and nature of the definition.
Structural Characteristics	how nodes, edges, relations, semantics or constraints are described.
Purpose	tasks or problems the representation aims to address.
Domain of Application	fields where the representation is employed.
Terminological Overlap	explicit mention of synonyms, equivalence or comparison with other terms.

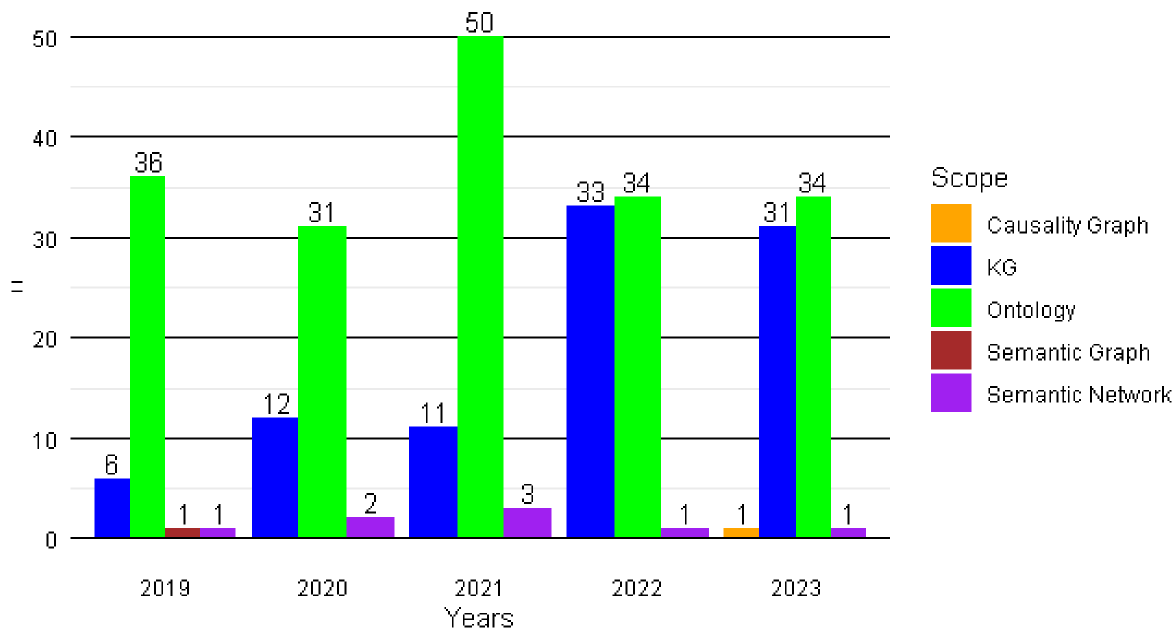
Source: prepared by the authors (2025).

(iii) Synthesis and comparative analysis: After coding, all evidence was aggregated by term and by category. This allowed the identification of patterns, recurring conceptual features and distinctions between the five selected representations. The coding results were compared across terms to answer the research questions (RQ1 and RQ2). To enhance reliability, the coding rules were applied consistently using the predefined protocol, and a subset of articles was double-coded by a second reviewer to minimize interpretation bias.

4 FINDINGS AND DISCUSSION

This section summarizes the main findings from the 288 studies aimed to address the research questions (RQs). First, we analyze some quantitative aspects of the retrieved studies, as illustrated in Figure 4. In general, the main scopes of the studies are as follows: (i) 185 focus on ontology; (ii) 93 on KG; (iii) 8 on semantic networks; (iv) 1 on causality graphs; and (v) 1 on semantic graphs. Since 2019, ontology has been the leading scope, followed by KG, although publications on KG have increased significantly since 2022. In contrast, causality graphs, semantic graphs and semantic networks show low representation. Overall, the findings indicate that ontology and KG have been dominating the research landscape.

Figure 4 - Quantitative studies per year



Source: prepared by the authors based on the study's data (2025).

After conducting a quantitative analysis, a qualitative analysis was initiated based on the literature retrieved from the SLR. Causality graphs are graph-based structures that model cause-and-effect relationships between variables (Gopalakrishnan *et al.*, 2023). Nodes represent variables and directed edges denote causal influence. These graphs formalize causal reasoning, distinguishing correlation from causation and support data-driven decision-making by providing a structured approach to analyzing causal systems.

Semantic graphs are structured representations where nodes denote key events and edges represent meaningful, contextual relationships between them (Dehghani; Asadpour, 2019). Unlike traditional graphs, they embed semantic depth, allowing the construction of coherent narratives from large datasets and supporting deeper interpretation of complex event sequences.

Next, semantic networks are analytical tools used to uncover meaning within structural data patterns. Common applications include textual analysis, scientometrics and theoretical models such as the Semantic Link Network (Arroyo-Machado; Torres-Salinas; Robinson-Garcia, 2021; Amirhosseini, 2023; Luo *et al.*, 2021; Park; Kim, 2021). When combined with Semantic Network Analysis (SNA), they reveal key concepts and themes by analyzing word co-occurrence patterns, offering insights into the semantic structure of complex datasets.

Afterward, KG are graph-based structures that represent real-world entities, concepts and their relationships, using subject-predicate-object triples (Chicaiza; Valdiviezo-Díaz, 2021; Cui *et al.*, 2023; Lu; Ichise, 2022). They support semantic organization and are foundational to AI applications such as semantic search, recommendations and question-answering (Q&A) (Liu *et al.*, 2023). Popularized by Google in 2012 with the phrase "things, not strings" (Cui; Zhang; Zheng, 2023; Sharma; Kanjilal, 2023), KG have, since, been widely adopted across domains like healthcare, finance and education. They often integrate ontologies to enhance semantic precision and interoperability (Brack *et al.*, 2022), enabling more meaningful and machine-readable knowledge representation.

Finally, ontologies provide formal, explicit specifications of shared conceptualizations (Gruber, 1993) as the main definition, followed by several studies, enabling structured representation, interoperability and reuse of knowledge across domains. Originating from philosophy, the term refers, in Computer Science, to abstract models of entities, concepts and their relationships, forming the backbone of semantic reasoning (Deus; Pereira, 2023; Löw *et al.*, 2022; Silva; Ribeiro, 2019; Zhao *et al.*, 2022). Ontologies address semantic interoperability by offering common vocabularies and supporting data integration, particularly in the Semantic Web, through languages like Web Ontology Language (OWL) (Gomes *et al.*, 2020; Roldán-García, 2021). Foundational models, such as BFO, UFO and DOLCE, enhance cross-domain interoperability and conceptual modeling (Amaral; Baião; Guizzardi, 2021). Ontologies are widely applied in AI, e-learning, decision support, recommendation systems and autonomous systems, where they standardize meaning and support dynamic knowledge evolution (Al-Aswadi *et al.*, 2023; Cosentino; Araújo; Crestani, 2024; Kondylakis *et al.*, 2021).

4.1 DISCUSSION

As noted in the introduction, ontologies remain the most prominent term in LIS, being frequently associated with domain modeling, as illustrated in Figure 4. In recent years, however, KG have experienced a notable rise in publications, while other terms, such as semantic graphs and semantic networks, have maintained a relatively stable usage. These latter terms are commonly employed to emphasize relationships between nodes, typically in textual data, where the structure highlights conceptual connections and meaning. Causality graphs, while also relational, are distinct in their focus on cause-and-effect systems.

In contrast, KG and ontologies play a central role in structured data contexts, particularly in tasks involving data integration and fusion, where preserving semantic consistency is essential. Their use of triples (subject-predicate-object) supports AI applications, including recommendation systems and Q&A platforms, by enabling machine-readable, semantically rich data. However, while KG excel at representation, they often lack foundational modeling capabilities and depend on ontologies, especially upper ontologies, grounded in philosophical principles, to establish shared, interoperable structures across domains. These findings reveal both convergence and divergence in graph-based terminologies, underscoring the dominant role of ontologies and KG in semantic reasoning and data-driven research.

Finally, Table 3 presents a comparative framework, highlighting the overlaps and distinctions among KG, ontologies, semantic networks, semantic graphs and causality graphs. While using graph structures to model relationships, they differ in focus.

Concerning RQ1 (Do authors refer to the same concept using different terms?), the analysis reveals a pronounced degree of terminological redundancy within the literature, particularly between ontologies and KG. These two constructs exhibit systematic conceptual entanglement: numerous studies describe systems architecturally implemented as KG while relying on ontological principles, such as formal conceptualization, class hierarchies and axiomatization, to define their semantic foundations. Conversely, other studies characterize ontology-based infrastructures as KG due solely to their operational use of graph-based data structures.

Table 3 - Summarized framework of concepts

Dimension	Knowledge Graph	Causality Graph	Semantic Network	Semantic Graph	Ontology
Definition	Graph of triples representing real-world entities and relations	Graphs that model cause-effect relationships	Network of concepts and relations to express meaning	Graph emphasizing semantic links between data	Formal specification of shared conceptualizati on
Purpose	Data integration, semantic AI and reasoning	Explain/predi ct effects from causes	Understand conceptual associations	Text and data mining and highlighting meaning	Structuring domain knowledge semantically
Structure	Triples: subject - predicate - object	Directed acyclic graph	Node-link (concept-	Similar to semantic	Classes, properties and

			relation-concept)	network	axioms (OWL)
Semantics	Formal	Often probabilistic/formal	Often informal	Variable (can be formal or informal)	Formal
Applications	Search, Q&A and recommendation	Medicine, economics and system modeling	Cognitive science, information retrieval and concept analysis	data enrichment	Semantic Web, enterprise modeling, Linked Data and AI
Related concepts	Uses ontologies for schema	May be enhanced by ontology for semantics	May overlap with semantic graph	May be implemented as KG or network	Used as schema for KG and others
Temporal / Causal	Limited	Central	Possible but limited	Rare	No, unless modeled explicitly
Modeling scope	Broad (cross-domain)	Specific (to causal processes)	Conceptual, often limited to a context	Text-specific or data-centric	Domain-specific or upper-level
Assumptions	Open-world	Closed-world or probabilistic	Varies	Varies	Typically open-world

Source: prepared by the authors (2025).

A similar pattern occurs between semantic networks and semantic graphs, which are frequently mobilized to characterize structures derived from textual corpora or conceptual co-occurrence patterns. In these contexts, the terminological boundary between the two is often blurred, with authors emphasizing relational semantics without specifying structural or methodological distinctions.

In contrast, causality graphs constitute an outlier: they preserve a coherent and domain-specific identity centered on the explicit representation of causal mechanisms. Across the corpus, authors consistently maintain this conceptual boundary, thereby reinforcing its methodological distinctiveness.

Taken together, these findings demonstrate that authors often employ divergent terminological labels to denote representations that are conceptually similar, or operationally indistinguishable, thus empirically supporting RQ1 and confirming the existence of a diffuse and overlapping terminological landscape.

With respect to RQ2 (What are the distinctions between these approaches?), the qualitative analysis clarifies the conceptual and functional boundaries among the terms. Causality graphs differ markedly from the other categories, as they explicitly model cause-and-effect relationships and rely on directed edges representing causal influence. Semantic networks and semantic graphs, although related, focus primarily on uncovering meaning in unstructured or semi-structured data, often using co-occurrence patterns or event-centric relations. In contrast, KG and ontologies play a central role in structured, semantically explicit modeling. KG rely on triples for machine-interpretable representation but lack the foundational axiomatic rigor provided by ontologies. Ontologies, particularly upper ontologies, introduce formal conceptual structures that enable interoperability, reasoning, and reuse across domains. These distinctions, summarized in the comparative framework (see Table 3), demonstrate that although all approaches share a graph-based foundation, they differ in purpose, representational rigor, and application domain. Thus, RQ2 is addressed by articulating the conceptual, methodological, and functional differences among the five terminological categories.

The comparative framework developed in this study offers practical value for researchers, system designers, and information professionals working with semantic modeling and graph-based representations. By clarifying the conceptual overlaps and distinctions among ontologies, KG, semantic networks, semantic graphs, and causality graphs, it supports the selection of appropriate modeling approaches and mitigates terminological ambiguity that may otherwise lead to methodological inconsistencies.

The framework also informs the design of semantic and AI-driven systems by distinguishing when formal conceptual models (e.g., ontologies) are required and when more flexible graph-based structures (e.g., KG) are sufficient. Additionally, it serves as a pedagogical aid in academic and professional training, promoting clearer conceptual understanding. Finally, it contributes to methodological standardization by enabling researchers to justify terminology choices more rigorously, thereby improving comparability and coherence across studies.

5 CONCLUSION

In the scientific literature, various terms are used to describe graph-based representations. The primary objective of this research is to consolidate and clarify these terms. To address this, an SLR was conducted to analyze the scientific literature within this scope. A total of 474 studies were retrieved, of which 288 were deemed eligible for further analysis following the SLR screening process.

The summarization phase highlighted key insights into these terms, leading to the conclusion that all graph-based data representations can be categorized as KG, whereas ontologies are primarily associated with shared, explicit modeling. Furthermore, while ontologies have consistently maintained representation in scientific publications, KG have experienced a notable increase in publications since 2022.

In conclusion, the guiding question has been answered, and the research problem outlined in this study is considered resolved. This study makes several contributions to the field of LIS. It provides a consolidated framework for understanding graph-based representations, addressing terminological ambiguities and offering insights into their practical and theoretical implications. By enhancing clarity in this domain, the study lays the groundwork for improved semantic data integration, knowledge management and AI applications.

However, several limitations should be acknowledged when interpreting the findings. The decision to restrict the review to studies published between 2019 and 2023 narrows the historical scope and may exclude foundational works that shaped earlier conceptualizations of the examined terms. Likewise, the reliance on three specific databases (WOS, LISTA and Brapci) while appropriate for LIS, limits the inclusion of perspectives from adjacent fields where graph-based representations are also extensively discussed.

Furthermore, although the review followed a structured extraction protocol and applied coding rules consistently, the interpretive nature of qualitative synthesis introduces an unavoidable degree of subjectivity, especially given the inconsistent use of terminology across studies. Finally, the analysis concentrates on conceptual descriptions rather than empirical performance or technical implementation, which narrows the applicability of the conclusions.

Even with these constraints, the systematic approach adopted provides a solid basis for understanding how the terminology is used in recent literature and offers a meaningful foundation for future research and practical developments in LIS and related fields.

Future work will focus on operationalizing the proposed framework by translating its conceptual distinctions into practical tools for data preparation workflows and visual exploration. This includes the development of structured resources that will support AI-driven knowledge representation and learning. This involves examining how different representational choices affect the performance, interpretability and generalizability of machine learning models. Additionally, efforts will be directed toward designing automated or semi-automated mechanisms for selecting representational strategies aligned with the requirements of specific AI tasks.

Finally, empirical and interdisciplinary studies will be essential for validating and refining the framework. Applying it across diverse real-world data preparation and semantic modeling scenarios will help identify necessary refinements and contribute to more coherent, adaptive and semantically robust approaches to knowledge organization in AI and related fields.

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