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Review

A comprehensive review of semantic web technologies supported life cycle management for road infrastructures

Rujie Zhang [a,b], Jianwei Wang [a,b], Haijiang Li [c], Xinhua Mao [a,b,*]

[a] *College of Transportation Engineering, Chang'an University, Xi'an, China*
[b] *Engineering Research Center of Highway Infrastructure Digitalization, Ministry of Education, Xi'an, China*
[c] *School of Engineering, Cardiff University, Cardiff CF24 3AA, UK*

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ABSTRACT

Aiming at a comprehensive understanding of semantic web technologies in enhancing digital intelligence of road infrastructure, 141 papers were selected for scientometric analysis and critical review. Research trends were visualized through co-authorship, co-citation, and co-word analyses, while critical reviews identified themes and limitations. Publication trends revealed growth peaks in 2016 and 2021 and shift toward journal-dominated outputs signaling maturation from exploratory methodologies to robust theoretical frameworks and practical validations. Co-authorship analysis revealed growing engineering-computer science collaborations, while co-citation analysis stressed foundational ontology methodologies. Keyword analysis identified essential themes including building information modeling, digital twins, and deep learning. Data exchange and semantic integration, knowledge management, and reasoning and simple querying were identified pivotal roles of semantic web technologies in road infrastructure. Subsequently, a preliminary framework was proposed synthesizing core components and key processes. Five limitations were identified: lack of comprehensive guiding framework and ontology development protocols; limited information integration and synchronization; insufficient automation; and weak capacity of logical inference and decision support. This paper contributes to the current knowledge body by providing insights into how semantic web technologies support the management of road infrastructures throughout life cycle and addressing concerns and limitations faced therein to offer suggestions for future advancement.

1. Introduction

As a fundamental component of the integrated urban transportation systems, the scientific and efficient management of road infrastructure throughout its life cycle is an indispensable prerequisite for the smooth operation of urban functions [1, 2]. However, this imperative persists as a multidimensional challenge due to the inherent complexity of coordinating multi-participants workflows, heterogeneous data sources, and cross-disciplinary decision-making processes across design, construction, operation, and maintenance phases.

Advances in information and communication technologies (ICTs) such as building information modeling (BIM), geographic information systems (GIS), internet of things (IoT), and artificial intelligence (AI), have brought new perspectives to this challenge and introduced transformative tools for digitizing and optimizing road infrastructure processes. For instance, BIM facilitated collision detection [3], construction projects optimization [4, 5], and traffic flow simulations [6]; GIS enabled spatial analysis and alignment optimization [7, 8]; IoT sensors embedded in pavements and bridges generate real-time structural health data [9, 10], and AI was utilized for road defects detection and predictive maintenance [11]. These ICTs have collectively enhanced the digitalization of road infrastructure and introduced new possibilities for optimizing the functionality and its long-term performance [6, 12, 13].

Despite these advancements, significant challenges remain in achieving holistic and semantically coherent information integration and intelligent infrastructure management. These stand-alone ICTs were characterized by a complex fragmented nature, adhering to disparate data standards [8, 14, 15], leading to inefficiencies in cross-domain reasoning [16–19] and knowledge-driven decision-making [20, 21]. These challenges manifest concretely when the coordination among road infrastructure design, structural engineering, geospatial analysis, maintenance strategies, and real-time sensor data gives rise to complex

* Correspondence to: Chang'an University Middle-section of Nan'er Huan Road Xi'an, ShaanXi Province 710064, China.
E-mail address: maoxinhua@chd.edu.cn (X. Mao).

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and heterogeneous information flows. For instance, during the integration of BIM component data with GIS regional information for road planning and design, while format conversion techniques enable the transfer of BIM's 3D geometric information and attribute data into GIS-compatible formats, fundamental heterogeneities persist in their conceptual frameworks, terminologies, and relational representations [7, 8, 22]. Similarly, in operational decision-making processes, where current road maintenance practices primarily rely on manual experience or simplistic threshold criteria, without comprehensively evaluating multidimensional factors including traffic volume, material aging, and environmental erosion. Moreover, cross-departmental collaboration and integrated decision-making remain inefficient due to systemic interoperability barriers, resulting in compromised assessment accuracy and suboptimal resource allocation throughout infrastructure life cycle management [23, 24].

Semantic web technologies have been recognized as a feasible solution to these concerns with respect to their capability to represent information as structured graphs and support data integration and complex search queries across diverse knowledge domains [25–27]. This approach established a prototype of knowledge graph formed by standardized links of interrelated information to promote machine understanding and processing of metadata and other large-scale information objects [28]. In the domains of architecture, engineering and construction (AEC), semantic web technologies have been leveraged as a complementary to BIM systems [26, 29]. Unlike the prevailing BIM data format standards (e.g., industry foundation classes (IFC)), which structure information such as project geometry and material attributes in a standardized way [8, 23], semantic web technologies enable formalized knowledge representation to resolve inconsistencies and ambiguous between entities and relationship descriptions [23, 30, 31]. Furthermore, cross-domain reasoning can be performed by leveraging the strengths of semantic web and ontologies in the field of knowledge representation and management [32], which allowing for interoperable heterogenous data from multiple sources while formalizing knowledge as an enabler for reasoning [33].

Emerging applications in AEC domains demonstrated these potentials to unify multidisciplinary data into actionable insights. For instance, IFC web ontology language (ifcOWL), which was designed and enhanced to retain the structural hierarchical concepts of IFC, but incorporating the data scalability, querying and reasoning, and reuse capabilities of the semantic web technologies [34, 35], has been further applied in areas such as code compliance checking [36] and city information modeling that merges BIM, GIS and IoT data [37]. In road infrastructure specifically, semantic web technologies have also been progressively introduced and investigated as means to: integrate information for cross-functional and spatial-temporal planning in highway projects [38], unify and interconnect lifecycle data spaces to facilitate decision making in highway asset management [24], enhance constraint information searching and rehabilitation project management of concrete bridges [18], as well as facilitate traffic forecasting through a knowledge representation-driven method [39].

The significance of semantic web technologies in the engineering domain has also been well-established in previous review studies. Earlier research has examined the research directions and advancements in semantic web technologies from multiple perspectives. As shown in Table 1, Pauwels et al. systematically analyzed the development and application processes of semantic web technologies in the AEC fields [26], emphasizing their indispensability for logic-based multi-source information integration. Zhong et al. conducted a scientometric analysis of ontologies in the construction domain, providing a comprehensive overview of the current research landscape and existing gaps [40]. While both studies adopted an engineering lifecycle perspective, their primary data sources were predominantly from the building industry. While Katsumi et al. organized and compared ontologies used in the transportation domain, analyzing their interrelationships through high-level taxonomies, they did not elaborate on their practical applications [41]. Lei et al. performed a detailed analysis of ontologies employed in road asset management, which aligns most closely with the objectives of this paper, yet there remains substantial scope for deeper exploration of the ontology technology stack itself [42]. While existing reviews provide valuable foundations, significant knowledge gaps remain:

Table 1
Representative published review papers related to semantic web and road infrastructure research.

References	Contents	Scope
Pauwels et al., 2017, Automation in Construction [26]	a) Interoperability b) Linking across domains c) Logical inference and proofs	Architecture Engineering Construction
Zhong BT et al., 2019, Automation in Construction [40]	a) Domain ontology b) Industry foundation classes c) Automated compliance checking d) Building information modeling	Construction
Katsumi M et al., 2018, Transportation Research Part C: Emerging Technologies [41]	a) Relationships between existing transportation ontologies b) High-level taxonomy of transportation-related concepts	Transportation
Lei X et al., 2021, Archives of Computational Methods in Engineering [42]	a) Public related information b) Implementation domains c) Ontology technique analysis	Road asset management

a) Domain-specificity limitations: Previous reviews predominantly focused on building engineering, while in-depth and structured investigations into the trends and barriers to the adaptability of semantic web technologies in the road infrastructure domain remain limited.
b) Holistic guiding framework deficiency: While current research substantiated the significance of semantic web technologies in road infrastructure domain, practical implementations were largely confined to isolated scenarios under singular circumstance. In light of the complex characteristics of road infrastructure, a semantically integrated technical framework that balances theoretical feasibility with engineering applicability was still underdeveloped.

From a broader perspective, there is a critical need to understand the state-of-the-art situation of semantic web technologies in the road infrastructure domain. To address these gaps, we proposed the following research questions, which formed the conceptual foundation of the paper:

RQ1. **:** What are semantic web technologies and what do they encompass? What are the prerequisites and domain-specific considerations for adopting semantic web technologies in road infrastructure?

RQ2. **:** What is the current research status and in which domains within the road infrastructure field might semantic web technologies be effectively utilized?

RQ3. : Which technical path or methodology should be followed during the application process?

RQ4. **:** What obstacles are encountered in practice and what should be worked on in the future to fully leverage the value of semantic web technologies?

These questions aimed to establish a technical and conceptual understanding of semantic web technologies, assess their current application landscape within the road infrastructure life cycle, explore the methodological pathways enabling their deployment, and identify practical challenges and future directions. Together, they are designed to bridge the gap between theoretical feasibility and engineering practice, and to guide a structured and comprehensive investigation into the role of semantic web technologies in advancing intelligent and integrated road infrastructure management.

Therefore, this paper aims to provide a comprehensive, up-to-date review of research on semantic web technologies in the road infrastructure domain. Through a scientometric and cluster analysis, this study conducted a visual examination of the current state and trends in the adoption of semantic web technologies within the road infrastructure industry, thereby fostering an understanding of the necessity and significance of their application in this field. Subsequently, a critical review was undertaken to identify achievements realized in practice and obstacles encountered, thereby providing insights to guide future research aimed at advancing the intelligent management of road infrastructure through its life cycle.

The remaining part of the paper was structured as follows: Section 2 described the research methodology. Section 3 presented a scientometric analysis of the collected papers. In Section 4, the results of the cluster analysis were summarized, and a critical analysis was given in Section 5 to identify the challenges of the research and future directions to be worked on. Section 6 outlined the conclusions.

2. Methodology

This paper classified and analyzed the research of semantic web technologies in road infrastructure domain through scientometric analysis and critical review. Quantitative insights were obtained and visualized through scientometric analysis while critical review was employed to identify research topics and obstacles along the development path. The research methodology in this paper consists of 5 main steps, as shown in Fig. 1.

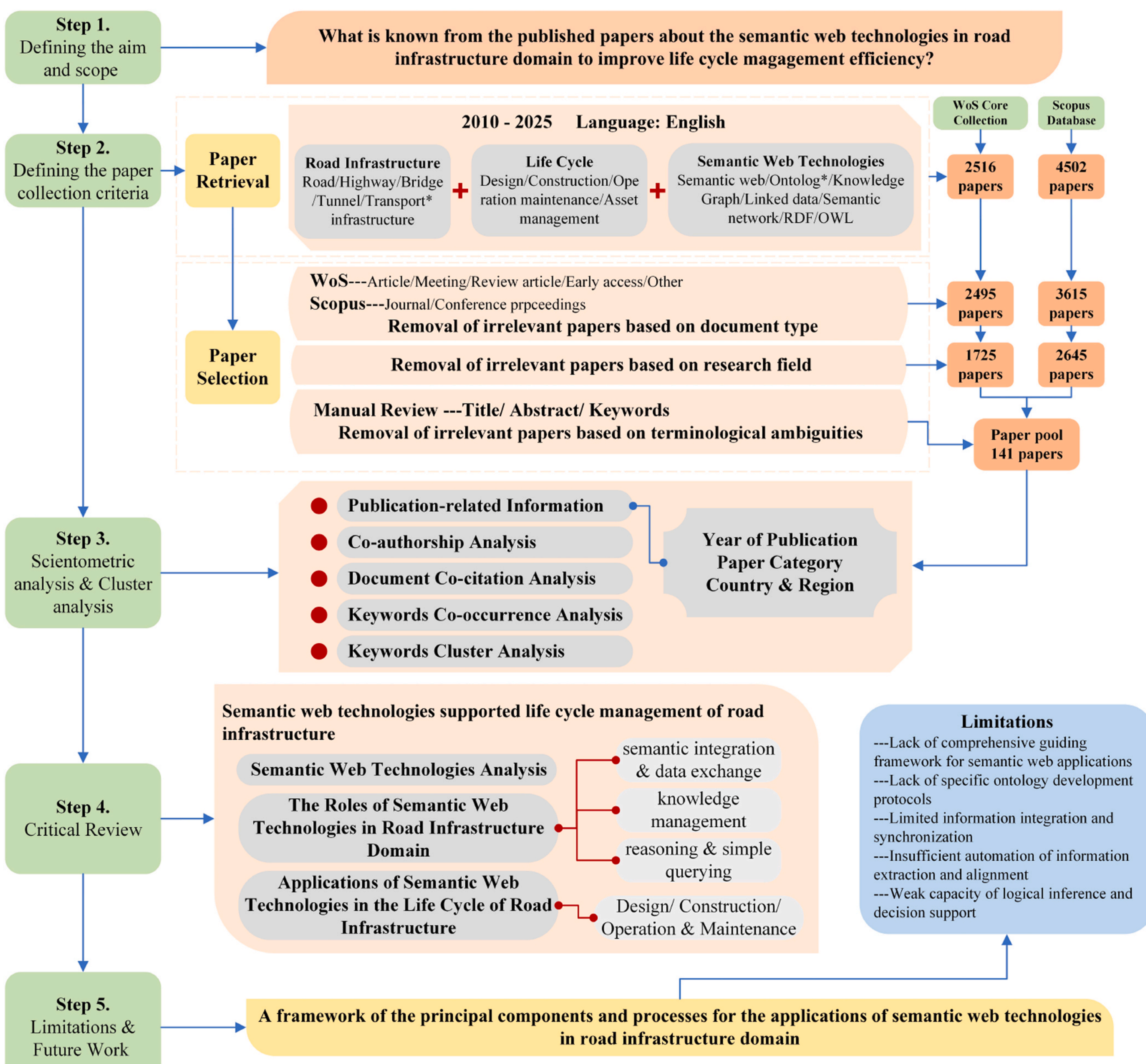

Fig. 1. Outline of research methodology.

2.1. Step 1: Defining the aim and scope

This paper was designed to examine the published papers and to determine the scope and implementation patterns of semantic web technologies in road infrastructure domain. Given the intricate nature of the road infrastructure systems, it was clarified that this research primarily focused on roads, bridges, and tunnels, while excluding railways, airport facilities and other structures. Notably, within the context of life cycle management specific to road infrastructure itself, studies related to traffic management and road user services during operational processes were excluded. Recognizing the strong relevance of semantic web-related technologies, terms such as “ontology” and “knowledge graph” were also enlisted in the following paper retrieval schema.

2.2. Step 2: Defining the paper collection criteria

2.2.1. Paper retrieval

The collected papers were primarily derived from topic searches conducted in the Web of Science (WoS) Core Collection and Scopus database. Boolean operators (AND, OR) were employed to refine the search strategy, balancing specificity and sensitivity, where the former restricting the thematic boundaries, and the latter ensuring that all relevant studies within the topic were covered. Aligned with the aim and scope delineated in Step 1, terms such as “highway”, “tunnel” and “bridge”, life-cycle phrases including “design”, “construction”, “operation”, and “maintenance”, as well as semantic web-related terms “ontology”, “knowledge graph”, “linked data”, “semantic network”, “Resource Description Framework (RDF)”, and “Web Ontology Language (OWL)” were inserted to the retrieval schema. The detailed search code was listed in Table 2, where the wildcard symbol ‘*’ denotes truncation for broader matching. Filters were applied to restrict publication dates from 2010 to 2025, and languages to English. This step generated an initial paper pool comprising 2516 papers from the WoS database and 4502 papers from Scopus database.

2.2.2. Paper selection

Due to the semantic ambiguities, papers unrelated to this study were also put into the paper pool after the initial searching step. To address this, a three-step screening process based on document type, research area and manual screening was implemented.

Firstly, preliminary screening by document type was conducted. In the WoS database, papers were filtered by types including article, meeting, review article, early access, and other. In Scopus database, papers were refined to journal and conference proceeding categories. This step reduced the remaining papers to 2495 (WoS) and 3615 (Scopus).

Secondly, papers clearly irrelevant to the study were excluded from a research field perspective, such as those papers exclusively specialized in medicine or philosophy. Notably, papers from computer sciences field were retained to preserve comprehensiveness of the dataset. Following this procedure, 1725 papers remained in WoS database and 2645 papers in Scopus database.

Finally, given persistent terminological ambiguities, for example, an instance of “road” can be understood as a physical pathway that facilitates travel or transportation, or as a metaphorical “means to achieve goals”, and “bridge” might denote physical infrastructure or conceptual linkages, while “ontology” is predominantly associated with philosophical research, the remaining papers were further subjected to meticulous manual review to assure both breadth and accuracy of the research data. The exclusion criteria were as follows:

a) Centered on non-road infrastructure (restricted in this paper), such as railways and airports.
b) Irrelevance to road infrastructure itself, such as studies on road user behavior, driving safety, driver assistance systems, or accident management.
c) Computer science studies lacking cross-domain relevance to road infrastructure, such as misinterpretations of terms like “highway” (as rapid development) or “bridge” (as conceptual links).
d) Studies solely addressing operational traffic management, such as traffic trajectory prediction in intelligent transportation systems (ITS), congestion control, autonomous driving, or vehicle service optimization. Noted that research centered on traffic flow prediction for route planning during the design stage were included.

After deduplication between two databases, 141 papers published between 2010 and 2025 were retained in the final paper pool for scientometric analysis and critical review.

2.3. Step 3 Scientometric analysis & Cluster analysis

Scientometric analysis, “a quantitative method of studying the process of the development of science” [43], employs mathematical techniques to shed light on how scientific research on specific topics, broader areas of inquiry, and even entire bodies of knowledge develop [44, 45]. CiteSpace adopted in this paper is a typical scientometric analysis toolkit designed for visualizing and analyzing trends and patterns in the scientific literature [45]. It provides various functions to facilitate the discovery of key pivot points and turning points in the development of the research domain [46].

In this paper, a scientometric analysis focusing on publication information, co-authorship, document co-citation, co-word analysis related to road infrastructure and semantic web technologies was conducted based on selected papers. Firstly, the publication-related information, including year of publication, category, country and region, were analyzed and visualized aiming to reflect the extent of research in different regions over different time periods. The co-authorship analysis then gave a micro-level collaboration among the authors of the study. Then key literature and dynamics of the research process were identified by documents co-citation analysis. The co-word analysis included the co-occurrence and clustering of keywords, which was used to clarify the hotness of the keywords studied and to classify the different research themes.

2.4. Step 4: Critical review

On the basis of the aforementioned visualization process, this part unfolded the tasks and issues of life cycle management of road infrastructure. Starting from the semantic web technology stack analysis, then the roles of semantic web technologies, in light of the status of their applications in the design, construction, operation and maintenance phases, sorting out the application landscape of semantic web technologies supported intelligent management of road infrastructures.

Table 2
The paper search code for semantic web applications in road infrastructure domain.

Search Code
((“Semantic web” OR ontolog* OR “knowledge graph” OR “linked data” OR “semantic network” OR RDF OR OWL) AND (“road infrastructure” OR highway OR road OR bridge OR tunnel OR “transport* infrastructure” OR “road design” OR “highway design” OR “bridge design” OR “tunnel design” OR “road construction” OR “highway construction” OR “bridge construction” OR “tunnel construction” OR “road operation” OR “road maintenance” OR “bridge maintenance” OR “tunnel maintenance” OR “road asset management” OR “infrastructure asset management”))

2.5. Step 5: Limitations & Future Work

Lastly, a framework of the principal components and processes for the applications of semantic web technologies in the road infrastructure domain was elaborated, combining all the issues to be considered in these steps, the critical review was performed to identify and analyze the limitations of the classified research themes and the future directions to be worked on.

3. Scientometric Analysis

3.1. Publication-related Information

This section provides a quantitative analysis of publication-related information for selected papers, including year of publication, journal/conference type and country/region, which answered the first part of RQ2.

Fig. 2 illustrates the distribution of publication types of the 141 papers from 2010 to 2025. As can be seen from the number of papers published each year, there was an overall fluctuating upward trend with 2024 marking the peak year, witnessing 24 published papers. It should be acknowledged that data for 2025 does not provide a comprehensive representation of the entire year due to the ongoing nature of the statistics collection period. Significant peaks were observed in 2016 and 2021, aligning with the digital transformation of the engineering industry. Beginning in 2016, the maturation of BIM-focused digital representation spurred a research shift toward the multi-source heterogeneous data integration [16, 40]. From 2021 onward, breakthroughs in machine learning (ML) and large language models (LLMs) catalyzed a surge in research focused on their deep integration with the engineering domain [33, 47]. Key topics include knowledge graph-driven parsing of unstructured engineering data and intelligent semantic knowledge management systems, reflecting a research focus transition towards practical application scenarios.

Regarding the publication types, journal articles constitute 63 % of the total, significantly surpassing conference papers (37 %). It is worth noting that in the early research stage, the conference papers made up a greater portion of published papers with studies primarily centered on technical path exploration and framework design, indicative of the initial exploratory stage of semantic web applications in road infrastructure domain. From 2016 onwards, the number of journal papers gradually exceeded that of conference papers and kept ahead of the curve in the following years, highlighting an evolving research emphasis shifting from methodological exploration to advancements in systemic theoretical innovation and practical engineering validation.

In terms of countries/regions, Fig. 3 gives the spatial distribution network of selected papers with 29 nodes and 30 links. The size of the nodes indicates the total number of papers published in that country/region, and the colors of the nodes tree rings correspond to the different years from 2010 to 2025. As can be seen from Fig. 3, China, United States, United Kingdom, Germany, and Australia occupied the top five positions in terms of the number of papers published with 65, 34, 17, 13 and 11 papers respectively. It can be noted that the sum of these five countries accounts for 77 % of the total number, indicating that the researchers from these countries have explored extensively and made outstanding contributions to the application of semantic web technologies in the field of road infrastructure.

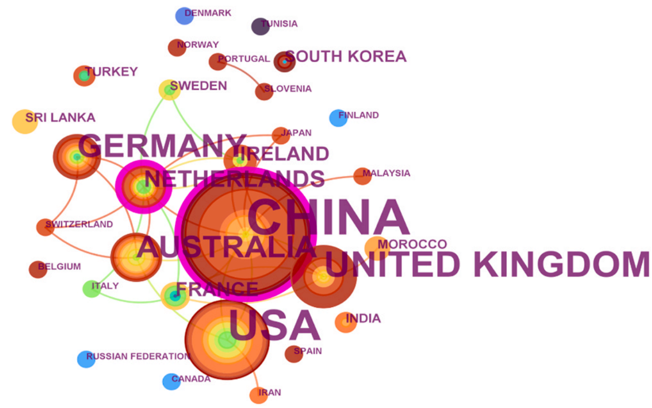

Fig. 3. The spatial distribution network of selected papers.

The analysis of the "betweenness centrality" (highlighted with a purple outer ring in Fig. 3), which evaluates the significance of nodes within a network, reveals that Netherlands held the highest position with a betweenness centrality value of 0.17. Following closely was China in second place with a value of 0.15, Australia in third (0.13), and United Kingdom in fourth (0.11). Their high betweenness centrality indicates their pivotal bridging roles in international collaboration networks. These countries exhibit prominent roles in applying semantic web technologies to road infrastructure research, demonstrating substantial influence in advancing this cross-domain collaboration. Notably, the Netherlands, despite its limited publication output (6 papers), maintains a relatively high betweenness centrality, underscoring its significant contribution to facilitating international cooperation within this field.

3.2. Co-authorship Analysis

The application of semantic web technologies in the domain of road infrastructure has witnessed the establishment of methods and theories accompanied by the ongoing development of scholarly collaboration. It

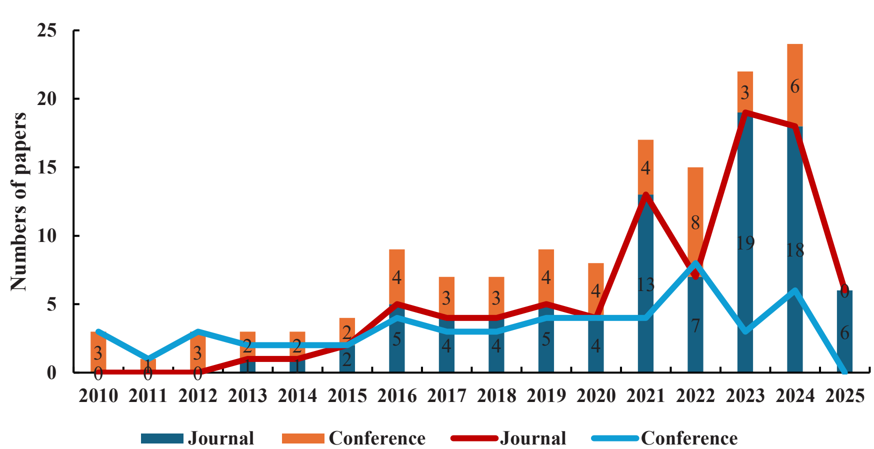

Fig. 2. The number and distribution of papers from 2010 to 2025.

is vital to examine the way academics engaged in collaboration to understand the frontiers of research and to identify outstanding scholars. Based on the collected 141 papers, this paper generated an author collaboration network and investigated the collaborative relationships among authors within this network through co-authorship analysis.

The co-authorship network was depicted in Fig. 4, with a total of 427 nodes and 979 links, where the nodes symbolize the authors, with their respective sizes denoting the number of published papers. The links signify collaborative interactions, while their colors correspond to distinct years in which the collaborations took place. Several research groups can be identified in the figure, and close collaborative relationships have been established between scholars within these groups.

One of the notable research groups was led by El-Gohary Nora, Kaijian Liu and Hu Xi, whose work primarily focused on the ontology-based information extraction and integration for bridge engineering, as well as semantic modeling of bridge performance degradation knowledge. Their team was among the early ones to apply semantic web technologies to data analysis in the construction field, establishing systematic research outcomes that have been extended into road infrastructure domain. Similarly, another significant group, comprising Li Ren, Jiang Shixin, and Yang Jianxi, primarily affiliated with Chongqing Jiaotong University, also specialized in bridges, their research mainly focused on knowledge extraction from inspection reports using ontologies and language models such as Bidirectional Encoder Representation from Transformers (BERT). The team led by Li Haijiang focused on engineering data analysis, information integration, and knowledge processing, with a dedication to developing intelligent computational engineering platforms. Their work in the road infrastructure domain encompassed knowledge-driven comprehensive maintenance decision-making for bridges and automated knowledge extraction with decision support solutions during tunnel design phases. A collaborative research team from the University of Shanghai and the University of Auckland, consisting of Hu Min, Wang Yields, Du Juan, Sugumaran Vijayan, and others, was oriented towards construction and operations management in the field of tunneling. Their research highlighted the indispensable role of semantic web technologies in enabling the convergence of data, objects, and knowledge layers within the digital twin framework. Another research group led by Anthony G. Cohn and Dimitrova Vania from the University of Leeds, with a primary focus on machine learning and knowledge representation for tunneling as well. Additionally, there was a research group led by Le Tuyen, which specialized in construction engineering, pavement engineering, and highway data analysis. Meanwhile, the work of Zhu Jun and collaborators focused on hybrid data-driven and knowledge-driven methodologies for decision-making in mountainous highway development, as well as highway bridge and tunnel construction and maintenance phases.

The co-authorship network revealed a clear pattern of collaboration among researchers, primarily centered around their respective institutional affiliations. Particularly, there was a noticeable lack of communication observed between different research groups. This phenomenon can also be detected by the betweenness centrality, which was calculated to be 0 for all nodes in the network and can only be identified as a key node if it is greater than 0.1. It is evident that there is a need to enhance the mutual collaboration among groups and scholars from diverse professional backgrounds.

3.3. Document Co-citation Analysis

Document co-citation analysis (DCA) can identify the key literature on multidisciplinary concepts and reveal the internal relationships and dynamics of the research paths [48]. Fig. 5 shows the generated document co-citation network with the screening criteria set to: time span 2010–2025, top 50 per slice (time slice length = 1), LRF = 3.0, L/N = 10, LBY = -1, and e = 2.0. The network comprises 170 nodes and 617 links. Each node represents a document identified by the first author and the year of publication. The size of each node corresponds to the number of times it has been co-cited. The presence of purple circles signifies that these nodes possess a betweenness centrality exceeding 0.1, indicating their significant involvement in bridging the cross-domain collaboration.

Table 3 lists the top 10 documents in terms of co-citation frequency. Most of these publications were related to domain ontology development. Among them, the article by Ren et al. ranks first for its methodical development of the bridge maintenance ontology (BrM ontology), one of the earliest ontologies in the field of bridge maintenance management using the Ontology Development 101 method, offering comprehensive reference processes for bridge maintenance knowledge management frameworks. Similarly, El-Gohary et al. constructed a basic ontology for infrastructure and construction process knowledge based on five concepts: entity, constraint, attribute, modality, and family. Works by Wu et al., Li et al., and Niknam et al., including the concrete bridge rehabilitation project ontology (CBRPMO), bridge structure and health monitoring ontology, and BIM shared ontology (BIMSO), encompass diverse perspectives ranging from construction processes to bridge maintenance and road entities. Notably, the seminal works by Gruber Thomas R and Uschold et al. from the 1990s still maintain high citation rates. Their papers have garnered significant recognition for their foundational contributions in defining ontology concepts, clarifying

Fig. 4. The co-authorship network of selected papers.

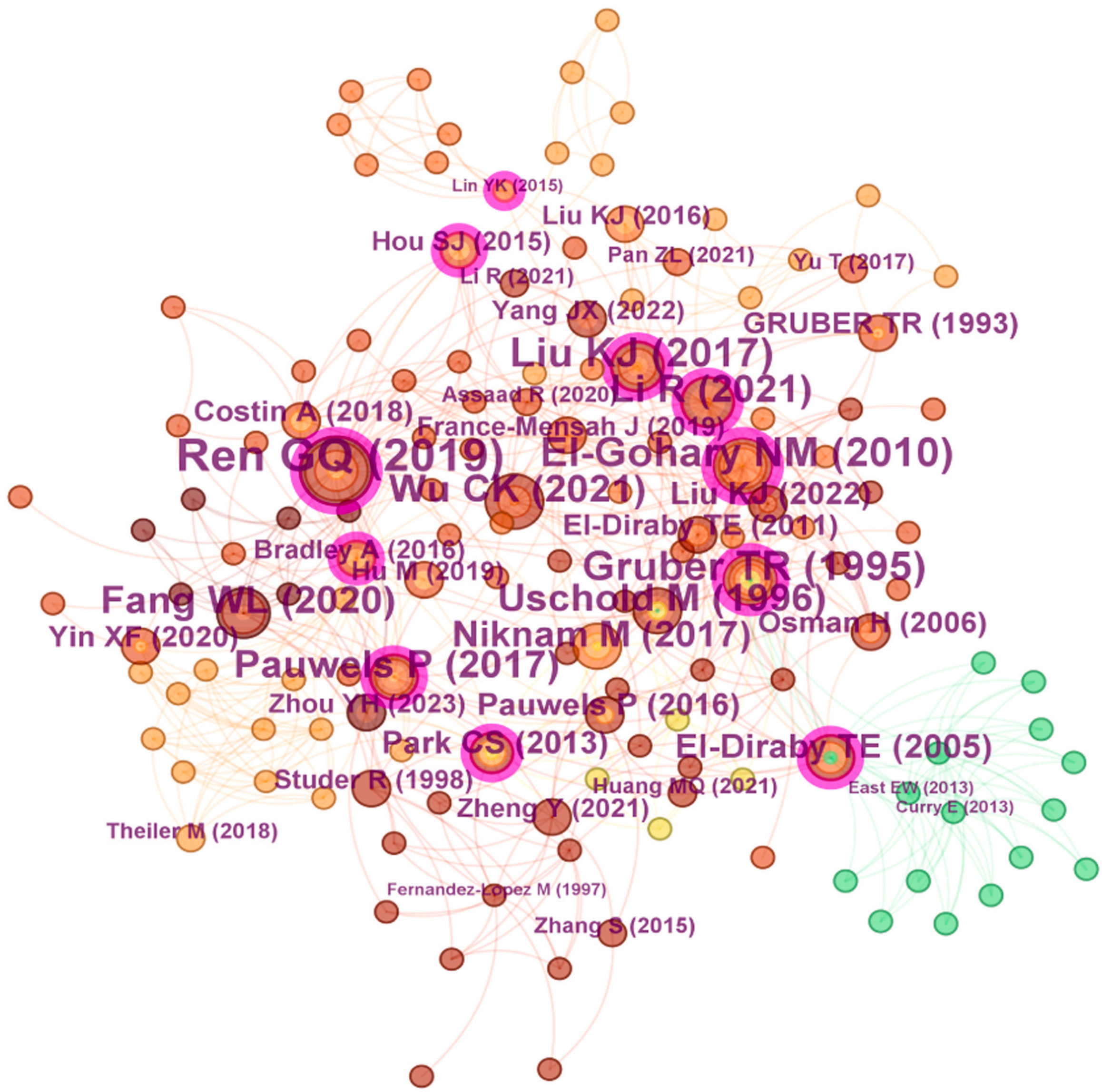

Fig. 5. The co-citation network of selected papers.

their role in knowledge sharing, and establishing methodological frameworks for ontology development. Furthermore, studies by Liu et al. and Fang et al. have innovatively integrated machine learning and computer vision algorithms with ontology for knowledge extraction and construction site hazard identification. Additionally, Pauwals et al.'s review on semantic web technology applications in the AEC domain has provided valuable guidance for subsequent research and technological advancements.

Table 4 gives the top 10 documents in terms of betweenness centrality in addition to those listed in Table 3. El-Diraby et al. first proposed a distributed ontology architecture for knowledge management in the highway construction domain, encompassing domain knowledge, application knowledge, and user knowledge. Bradley et al. systematically reviewed the application of BIM in the infrastructure field, recommending the use of semantic web technologies to link and integrate information resources within the domain. Park et al. pioneered the integration of BIM, augmented reality, and ontology for construction defect management. Finally, Hou et al. extended the application of semantic web technologies in the engineering field to low-carbon aspects of structural design. Their proposed Ontology for Sustainable Concrete Structure (OntoSCS) framework demonstrates the potential of ontology and semantic web rules in knowledge-driven systems.

3.4. Keywords Co-occurrence Analysis

Statistical analysis of keyword frequency and centrality can provide clear insights into understanding and identifying research hotspots in the field. Therefore, keywords were extracted from the selected 141 publications and imported into CiteSpace for co-occurrence analysis. At the same time, to verify the credibility of the data, the synonymous terms were merged in the order of keyword frequency. For example, "semantic web technologies" and "semantic web technology" were merged into "semantic web", "building information modelling", "building information systems (bim)", "building information modeling (bim)" into "building information modeling". It was noted that "BIM" was used to represent "building information modeling" in CiteSpace for a clear display. Similarly, "industry foundation class (ifc)", "industry foundation classes" and "industry foundation classes (ifc)" were merged into "IFC". The keyword co-occurrence network obtained has 374 nodes and 1472 links under the screening criteria: time span 2010–2025, time slice length = 1, g-index (k = 100), LRF = 3.0, L/N = 10, LBY = -1, and e = 1.0 (shown in Fig. 6).

Each node represents a keyword, and its size denotes the frequency of the keyword occurrence in the data set. The links represent the correlation between keywords, and their color represents different years

Table 3
Top 10 co-citated documents sorted by count.

Cited references	Count	Centrality	Contents
Ren GQ, 2019, Advances in Engineering Software [49]	15	0.18	Proposed a holistic ontology-based framework for bridge maintenance.
El-Gohary NM, 2010, Journal of Construction Engineering and Management [50]	12	0.26	Presented an ontology for the infrastructure and construction domain using five concepts of entity, constraint, attribute, modality, and family.
Liu KJ, 2017, Automation in Construction [51]	11	0.13	Proposed an ontology-based semi-supervised conditional random field method for information extraction from bridge inspection reports.
Gruber TR, 1993, Knowledge Acquisition [52]	11	0.21	“An ontology is the specification of a vocabulary of representations - definitions of classes, relations, functions, and other objects - in the domain of shared discourse”.
Wu CK, 2021, Automation in Construction [18]	10	0.04	Presented the concrete bridge rehabilitation project ontology (CBRPMO) to improve information integration and constraint management.
Uschold M, 1996, The Knowledge Engineering Review [53]	9	0.06	Proposed methodology for ontology development and evaluation.
Li R, 2021, IEEE Transactions on Industrial Informatics [19]	9	0.11	Designed a bridge structure and health monitoring ontology to integrate heterogeneous sensor data for structural health monitoring systems.
Fang WL, 2020, Automation in Construction [17]	9	0.05	Integrated computer vision algorithms and ontology to enable the development of knowledge graphs for automated hazard identification on construction sites.
Pauwels P, 2017, Automation in Construction [26]	9	0.12	A comprehensive review on the application of semantic web technologies in the architecture, engineering, and construction (AEC) domain.
Niknam M, 2017, Automation in Construction [27]	8	0.01	BIMSO (BIM shared ontology) was developed to enable semantic representation of building information and to serve as an extensible foundation ontology for the development of different ontologies in the building domain.

from 2010 to 2025. The top 10 high frequency occurring keywords were: “ontology”, “knowledge graph”, “semantic web”, “BIM”, “decision support”, “bridge maintenance”, “knowledge management”, “bridge inspection”, “digital twin”, “deep learning”.

It is worth noticing that, besides the research theme semantic web technologies related keywords “ontology”, “knowledge graph”, “semantic web”, the keyword “BIM” appeared with the highest frequency. BIM was regarded as a digital asset for information exchange among stakeholders in the AEC industry [58] and the foundation of digital transformation [59]. By leveraging 3D parametric modeling, BIM established the digital foundation for road infrastructure. Under the semantic web framework, the transformation and semantic representation of BIM data (e.g., converting IFC to OWL) bridged the gap between engineering semantics and machine-readable knowledge, thereby facilitating data exchange and integration across information models and domains [8, 27, 60]. Simultaneously, the keyword “digital twin” also appeared with significant frequency. Digital twins marked another critical technological leap in the engineering field following BIM [61]. They created real-time dynamic mapping models of physical entities in virtual space through digital means, achieving data interaction and synchronized optimization between physical and virtual entities [62]. Semantic web technologies played a pivotal role by linking data, objects, and knowledge in digital twin frameworks [63]. Through semantic modeling, knowledge fusion, and intelligent reasoning, the digital twin systems were endowed with structured knowledge representation and dynamic decision-making capabilities [10, 64]. Furthermore, the keyword “deep learning” has gained increasing attention since 2020. Its applications mainly focused on two aspects: the semantic conversion and knowledge extraction from unstructured data such as industry standards, specifications, and historical inspection reports [9]; and the integration of deep learning algorithms with ontologies to develop intelligent decision-making systems driven by both data and knowledge [65].

Table 4
Top 10 co-citated documents sorted by betweenness centrality (not included in Table 3).

Cited references	Count	Centrality	Contents
El-Diraby TE, 2005, Journal of Construction Engineering and Management [54]	7	0.20	Proposed a distributed ontology architecture for cross-domain knowledge exchange in highway construction.
Bradley A, 2016, Automation in Construction [55]	4	0.19	A systematic review on infrastructure and construction BIM.
Park CS, 2013, Automation in Construction [56]	6	0.14	Proposed a conceptual system framework integrating BIM, augmented reality (AR), and ontology for construction defect management.
Hou SJ, 2015, ENERG BUILDINGS [57]	4	0.11	Proposed a prototypical system OntoSCS (Ontology for Sustainable Concrete Structure) for structure design decision support.

3.5. Keywords clustering analysis

To further illustrate the research topics of semantic web technologies in the field of road infrastructure, this study clustered the keywords on the basis of Fig. 6 and the keyword clustering graph (Fig. 7) was generated using the built-in algorithm of Log-likelihood rate (LLR) in CiteSpace.

As seen in Fig. 7, 11 significant keyword clusters were identified, namely cluster #0 “bridge maintenance”, cluster #1 “ontology model”, cluster #2 “building information modeling”, cluster #3 “information extraction”, cluster #4 “knowledge representation”, cluster #5 “road network”, cluster #6 “intelligent bridge management”, cluster #7 “computer vision”, cluster #8 “infrastructure system”, cluster #9 “risk management”, cluster #10 “digital project delivery”.

Observing these 11 clusters, we can find that “ontology model” primarily focused on diverse application forms and foundational modeling techniques related to semantic web technologies. Clusters such as “bridge maintenance”, “building information modeling”, “road network”, “intelligent bridge management”, “infrastructure system”, “risk management”, and “digital project delivery” were concerned with specific application scenarios in different life cycle stages, categorized under the application layer. Similarly, the cluster “computer vision” in this study was mainly applied to construction scenarios and the

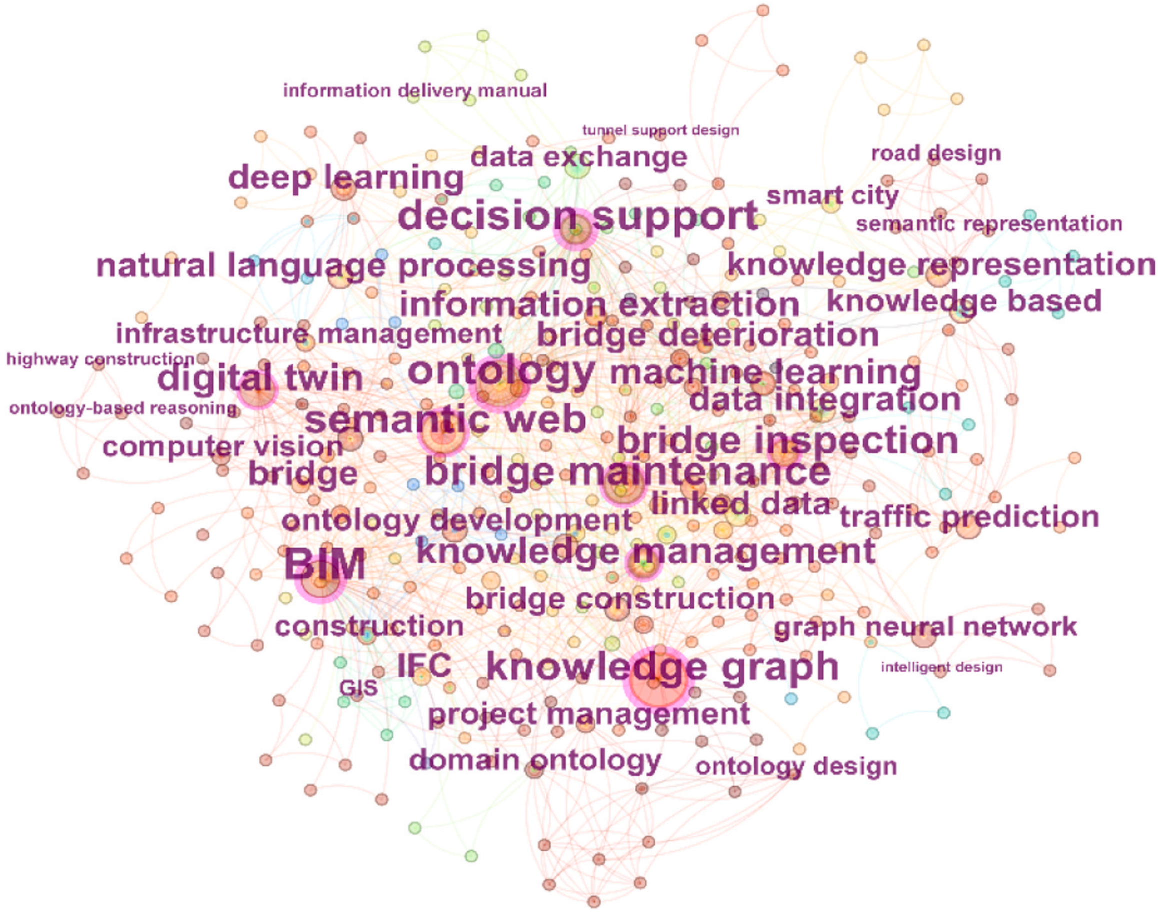

Fig. 6. The keywords co-occurrence network of selected papers.

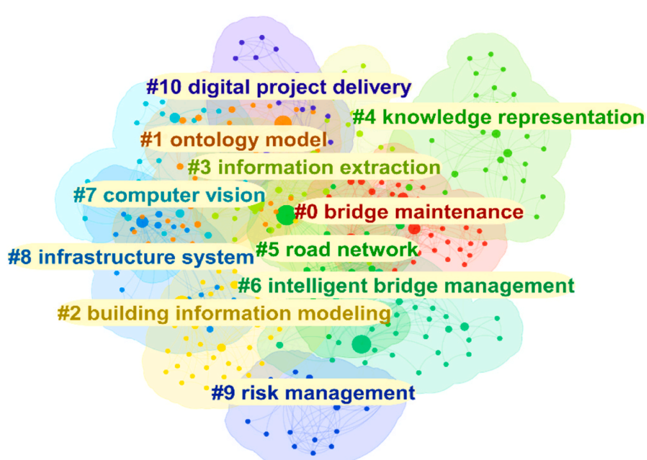

Fig. 7. The keywords clustering graph of selected papers.

interpretation of surface defects in concrete and tunnel structures, and thus was also classified within the application layer. While "information extraction" and "knowledge representation" were dedicated to information management in the aforementioned scenarios, highlighting the roles that semantic web technologies played in these processes.

Therefore, corresponding to the first two research questions mentioned in Section 1 (RQ1, RQ2), these 11 clusters would be analyzed from three perspectives in Section 4: semantic web technologies analysis, the roles of semantic web technologies in road infrastructure domain, applications of semantic web technologies in the lifecycle of road infrastructure.

4. Semantic web technologies supported life cycle management of road infrastructure

4.1. Semantic Web Technologies Analysis

This part answered the former part of RQ1 by offering a well-organized overview of semantic web technologies.

Semantic web is a generic framework for making data on the web machine-readable [66]. Establishing effective methods for sharing, discovering, integrating, and reusing data is the objective of this area of application. During the development and advancement of semantic web technologies, terminologies including semantic network, linked data, knowledge graph, ontology, RDF, OWL, etc. were commonly employed and might lead to confusion when selecting appropriate technologies for a certain situation. Fig. 8 elucidated these terms to facilitate a clear understanding of the implementation of semantic web technologies in the road infrastructure domain. Initially, semantic networks were suggested as a form of knowledge representation comprised of interconnected nodes and edges [67]. However, they were hindered by the absence of specific definitional standards. To address this issue and provide label definitions for nodes and edges, RDF [68] and OWL [69] were then proposed successively. Following this, the terms semantic web [70] and linked data [71] were introduced to better characterize the relationship between resources and data in the world wide web. The former was more inclined to express the relationship between concepts, while the latter emphasized interlinking among multiple data sets. Knowledge graph [72] served as an expanded industry implementation of these ideas nowadays, consisting of an ontology [73] as the schema

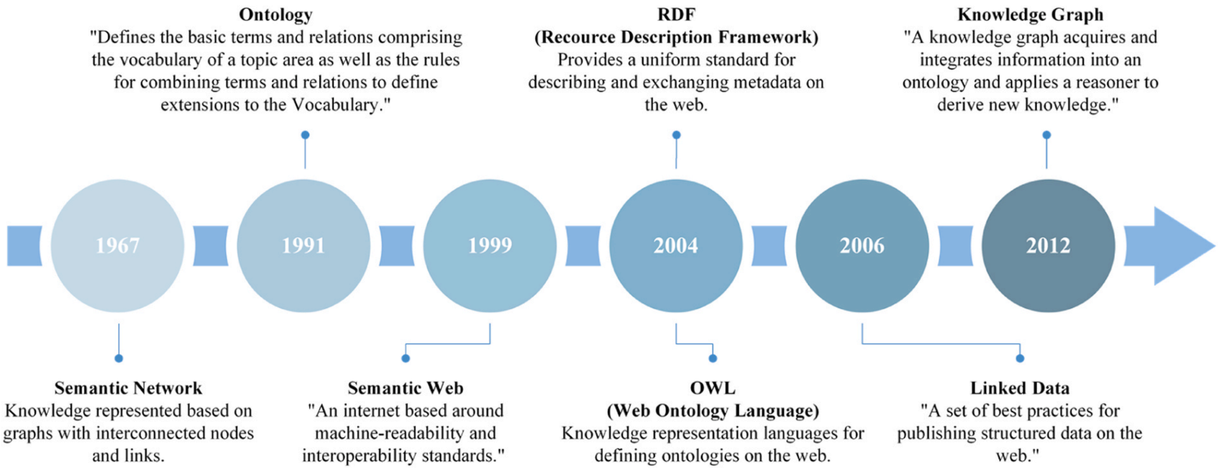

Fig. 8. Terminologies related to semantic web technologies.

layer and structured datasets that are compatible with the RDF data type.

Ontology, a philosophical concept, was introduced into computing domain in the early 1990s. Tom Gruber defined an ontology as an “explicit specification of a conceptualization”, specifically referring to the hierarchical organization of classes and the relationships between entities [52]. Ontologies served as the basic tools for integrating, distributing, and discovering information within the stack of the semantic web [74]. The goal of ontologies was to capture knowledge, provide common understanding, and identify mutually accepted vocabularies for specific domains, and to support sharing and interaction with other related domains [26]. Table 5 displayed a representative selection of ontologies derived from the collected papers. In general, ontologies have been developed for all stages of the roads, bridges and tunnels. For example, El-Gohary et al. proposed a distributed ontology architecture (HiOnto) for cross-domain knowledge exchange in highway construction [54]. Likewise, HCIOntology [75] was devised with the purpose of retaining and managing inspection knowledge at road construction phase. Niknam et al., on the other hand, focusing on pavement management, created the RSO and RMO [76] by using a shared ontology approach to model the road infrastructure knowledge domain based on the BIMSO proposed in 2017 [27]. IHP-Onto [38] mainly served to provide representations that could be used to support integrated planning tasks for road asset management. Within the field of bridge engineering, the notable ontologies include CBRPMO [18], which focused on improving the integration, reasoning, and retrieval of project information in the constraints management of bridge rehabilitation projects, as well as BMDO [77] and BrMontology [49], which primarily concentrated on maintenance processes. OntoETS was specifically designed to evaluate design alternatives for tunnel systems [78].

An overview of the development methodologies adopted for the representative ontologies was also presented in Table 5, including Ontology Development 101 [79], The NeOn Methodology [80], Methontology [81], and Uschold and Gruninger [53]. Detailed steps of these methods were illustrated in Fig. 9. These methodologies comprehensively addressed critical considerations in the ontology development process, allowing for the selection of a single method or a combination of multiple approaches based on specific scenarios and requirements. Notably, Ontology Development 101 emphasizes the reuse of existing ontologies, as ontologies are fundamentally built for reusability. As can be seen in Table 5, nearly half of the ontologies reused existing ontologies and it is anticipated that this trend will intensify with ongoing

Table 5
Respective ontologies selected from collected papers.

Ontologies	Methodology	Descriptive Language	Scopes	Ontology Reuse	Validation	
					Semantic validation	Syntactical validation
CBRPMO (Concrete Bridge Rehabilitation Project Management Ontology) [18]	Ontology Development 101	OWL syntax	Concrete bridge Rehabilitation	—	competency questions Consulting experts	Built-in reasoner
HiOnto (Highway Ontology) [54]	—	OWL	Highway Construction	e-COGNOS ontology	Competency questions Industry survey	—
BIMSO (BIM Shared Ontology) [27]	The NeOn Methodology	RDF/OWL	AEC-FM	—	SPARQL query language	—
BMDO (Bridge Maintenance Domain Ontology) [77]	—	OWL	Bridge Maintenance	—	—	Built-in reasoner
BrMontology (Bridge Maintenance Ontology) [49]	Ontology Development 101	OWL	Bridge Maintenance	—	Consulting experts	Built-in reasoner Case study
RSO (Road Shared Ontology) RMO (Road Maintenance Ontology) [76]	—	OWL 2	Pavement Maintenance	Time ontology	SPARQL query language	—
OntoETS (Ontology of Energy-Tunnel Systems) [78]	Ontology Development 101	OWL	Tunnel Design	—	by comparing, reusing, and merging the existing ontology	Built-in reasoner SWRLTab plugin
IHP-Onto (Integrated Highway Planning Ontology) [38]	Methontology Uschold and Gruninger	RDF/OWL	Highway Planning	e-COGNOS ontology	task-based, data-driven, and criteria-based evaluations	Automated consistency checking
HCIOntology (Highway Construction Inspection Ontology) [75]	—	RDFS/OWL	Highway Construction	—	Pilot Project for Testing	—

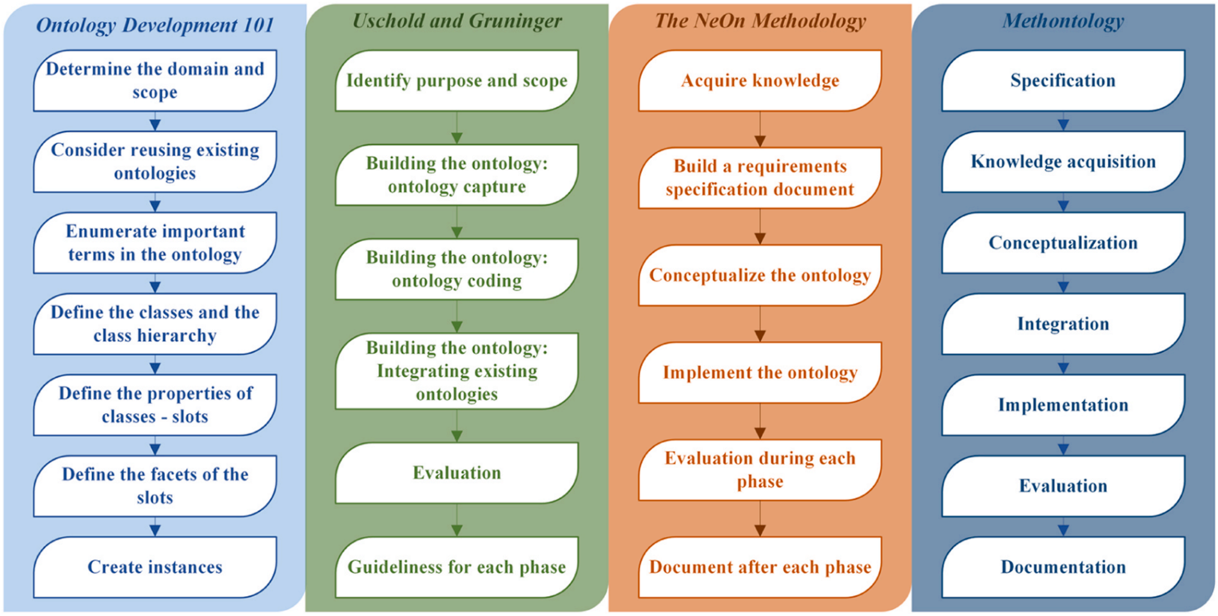

Fig. 9. Methodologies for ontology development.

development and refinement of industry-specific ontologies. The e-COGNOS ontology [82], mentioned twice in Table 5, was derived from the IFC framework, defined resources, actors, processes, and products involved in the interconnected building construction process [38], which was informative for the workflow definition. In addition, validation remained an integral step in ontology development, typically achieved through expert review and built-in reasoners and case-based validation to guarantee consistency at both semantic and syntactic level.

In terms of description languages and storage models, RDF, RDF Schema (RDFS) and OWL were found more widely used from collected papers (Table 5). RDF was inherently a data model that provides a unified standard for describing resources on the web [83], represented formally as a subject, predicate, object (SPO) triple for describing concrete things and relationships [84]. RDFS was designed as the extension and enrichment of the RDF vocabulary for describing resources and relationships, defining classes, properties and relationships on the basis of RDF, and constraining resources through the domain and range of properties [85]. Hagedorn et al. converted the data in the road asset management database to RDF format to support the linking of data to the IFC model and to industry ontology instances, but there were still problems with ontology retrieval and alignment [86]. OWL and later improved version of OWL 2 were released to address these aspects, adding predefined vocabularies that can declare resource equivalence, attribute transferability, mutual exclusivity, functionality, symmetry, etc. to describe resources, further enriching RDFS with better semantic expressiveness. The semantic traffic analytics and reasoning for city (STSR-CITY) ontology built by Lecue et al. was based on OWL 2 expressing language, which guaranteed the accuracy, efficiency, and flexibility in exchanging and integrating heterogeneous data from multiple sources [87].

In addition, knowledge graph was seen as a new framework of thought derived from the semantic web, consisted of instances of classes described in ontologies which was more domain specific and often industry-oriented [88]. The construction of knowledge graph was typically based on ontology design, encompassing steps such as information extraction, knowledge integration and updating, and knowledge storage [33, 89]. Ontology design, also referred to as the schema layer design of knowledge graph, was often conducted manually by integrating domain expertise to achieve semantic unification through the fusion of multi-source heterogeneous data [90] (e.g., structured sensor data and unstructured text). For example, an ontology base has been developed by extending the construction operation building information exchange (COBie) standard and incorporating maintenance experience to support the representation of operational knowledge for electromechanical equipment in tunnels [10]. Information extraction involved deriving structured information (entities, relationships, and attributes) from semi-structured or unstructured data to form the fundamental units of knowledge [33]. Common methods included rule-based, statistics-based, and machine learning-based approaches. For instance, rule-based systems and natural language processing (NLP) techniques were employed to extract entity relationships in tunnel support design from regulatory documents, while deep learning models (e.g., BERT) combined with statistical methods were used to mine non-classified relationships from literature or design schemes [91]. For knowledge integration and updating, semantic similarity calculation (e.g., text matching based on word embeddings) was frequently adopted for entity alignment [92]. Real-time sensing data was introduced to enable dynamic updates of subgraphs [93], while graph embedding techniques and semantic query languages (e.g., SPARQL Protocol and RDF Query Language, SPARQL) were utilized to optimize link prediction and decision generation [94]. Notably, the storage and computational architecture of knowledge graph was increasingly integrating with digital twin technologies [64]. The "entity-relationship-attribute" graph model naturally positioned knowledge graph as an enabler for achieving a universal digital twin (UDT) [95].

Research on knowledge graph in the road infrastructure domain has been rising steadily since 2021, reaching a phase of deepened application by 2023 and 2024, covering the entire lifecycle of design, construction, and maintenance. Through multimodal data integration, visual representation, and rule-based reasoning and decision support, knowledge graph has provided technical support for the intelligent advancement of road infrastructures. In tunnel engineering, knowledge graph integrated lifecycle data of shield tunnels, facilitating the fusion of computer vision-based object detection with maintenance planning. Additionally, the combination of a tunnel risk knowledge graph (TRisKG) and generative pretrained transformer (GPT) has achieved precise responses in tunnel risk question answering systems [96]. For bridge management, knowledge graph supported similarity calculation and recommendation of low-carbon construction solutions [92] while optimizing maintenance strategies through node classification and parameter clustering [94]. In highway engineering, knowledge graph designed for mountainous highway scenario leveraged spatial semantic constraint rules to accelerate digital twin modeling [97], and cloud model-based data trace improved efficiency in highway construction anomaly control [98]. Furthermore, knowledge graph also enabled condition prediction and fault tracing in electromechanical equipment operations [10] and enhanced traffic flow prediction efficacy by integrating expert knowledge with graph convolutional networks [99].

4.2. The Roles of Semantic Web Technologies in Road Infrastructure Domain

This part addressed the latter portion of RQ1 by analyzing the domain-specific imperatives for adopting semantic web technologies in road infrastructure domain. The digital transformation of road infrastructure domain has evolved from fundamental data collection to knowledge-driven and intelligent decision-making, presenting multifaceted challenges throughout the entire lifecycle [100, 101]. During the design phase, collaborative optimization was imperative to resolve multi-disciplinary parameter coupling conflicts [38, 91], while the construction phase demanded rigorous control over project scheduling and safety management due to the linear engineering characteristics and unique environmental constraints [102]. For the operation and maintenance phase, time-sensitive decision-making required the integration of massive sensor data with unstructured empirical knowledge [103]. Key challenges include cross-phase data fragmentation (e.g., incompatibility between BIM and GIS formats [104]), difficulty in implicit knowledge reuse (e.g., expert experience concealed in static documentation [105]), and efficiency bottlenecks stemming from manual reliance in real-time decision-making [106]. Semantic web technologies addressed these issues through unified ontology models and semantic mapping rules, thereby transforming multi-source heterogeneous data into machine-interpretable semantic networks. Particularly, RDF triples enabled dynamic associations between design parameters and operational metrics, while the semantic web rule language (SWRL) rules converted engineering specifications into executable logic [105]. This not only eliminated data silos but also enabled cross-phase reasoning (e.g., correlating tunnel defects with maintenance strategies [89]) and empowered real-time knowledge services (e.g., knowledge graph-enabled bridge inspection Q&A systems [107]).

Specifically, data exchange and semantic integration were found to be initial considerations for the adoption of semantic web technologies in the field of road infrastructure [26]. Effective data integration and exchange not only at the syntactic level but also at the semantic level were prerequisite for intelligent management and scientific decision-making [21, 108]. With this objective, the ontological conceptualizations of the domain were crucial components of the semantic web mechanism as these ontologies provide common vocabularies for the integration of heterogeneous sources [109]. Three primary implementation patterns were observed: a) Horizontal integration, where domain ontologies that unified fragmented lifecycle data and resolved the ambiguity and semantic inconsistency dilemma found in early open data standards developed using object-oriented modeling techniques (e.g., IFC and LandXML) [24]; b) Vertical integration, exemplified by IFCInfra4OM ontology that connected BIM-derived design parameters with real-time operational monitoring data [23]; c) Scenario-specific applications, including construction risk reasoning (e.g., tunnel subsidence early warnings [110]), semantic enrichment of BIM models [27], traffic scenario modeling [111] and sensor data harmonization in ITS [112]. These ontology-driven mechanisms established unified vocabularies crucial for coherent decision-making across the fragmented infrastructure systems.

Meanwhile, semantic web technologies have demonstrated substantial potential in knowledge management by transforming unstructured lifecycle data (e.g., historical maintenance reports, traffic monitoring videos) into structured knowledge for evaluating, predicting and managing the long-term performance of road infrastructures [113–117]. Semantic web technologies, as powerful knowledge management tools, enable semantic representation through three key applications: a) Information extraction frameworks, as demonstrated by Liu and El-Gohary's ontology-based system for bridge deterioration prediction using text mining and semi-supervised learning [51, 116]; b) Cross-domain knowledge integration, exemplified by Fang et al.'s computer vision-ontology hybrid for construction hazard identification [17]; c) Formalization of expert knowledge, such as Hu et al.'s ontology for structural deficiency modeling and Chen et al.'s BIM-compatible knowledge model automating facility inspections [47, 118]. By interlinking domain concepts and embedding reasoning rules, semantic web technologies enabled the explicit and machine-interpretable expression of both codified standards and tacit expert knowledge, effectively addressing the complexity and heterogeneity inherent in infrastructure knowledge management.

Reasoning and simple querying were also strengths of the semantic web technologies, where the use of an inference engine allows extra information to be inferred from RDF and OWL through simple Description Logic (DL) principles, which provided new solutions for the intelligent management of road infrastructures. To automatically compute and fill in missing relationships and attribute values, Zhang et al. employed ontology reasoning and predefined SWRL rule-based reasoning in the establishment of a bridge maintenance knowledge graph and performed consistency checking through a global reasoner [77]. Similarly, Yu et al. encoded tunnel operation and maintenance knowledge in the form of inference rules by defining SWRL. Based on the existing knowledge in the ontology library, the engine parses these inference rules to infer new knowledge and update and extend the ontology library, thus forming a closed loop of knowledge management [119]. In addition, decision making can also be supported by logical reasoning-based automatically information inference in infrastructure domain for vulnerability identification [120] and inter-asset management [121]. And these logical reasoning and proof processes based on semantic web technologies allow for the automatic generation of proofs of inferences, which to some extent compensates for the interpretability deficiencies of current artificial intelligence approaches such as machine learning [122].

4.3. Applications of Semantic Web Technologies in the Lifecycle of Road Infrastructure

Analysis of the 141 collected papers revealed that the application of semantic web technologies in the field of road infrastructure spans the entire life cycle. In response to RQ2 in Section 1, this part clearly mapped the applications of semantic web technologies across life cycle

Table 6
Distribution of semantic web technology adoption at different stages and their representative research.

Stages & Numbers	Specific Application	Representative Research
Design (20)	Collaborative Design	[8], [38], [78], [91], [100], [123], [124], [125], [22]
	Automated Compliance Checking	[105], [126], [127]
Construction (18)	Quality Control	[75], [102], [128], [129], [130]
	Safety Management	[17], [60], [93], [96], [131], [132], [133], [134]
	Schedule Management	[135], [136], [137], [138]
Operation & Maintenance (72)	Inspection & Condition Assessment	[19], [47], [86], [90], [107], [113], [122], [139], [140], [141], [142], [143], [144], [145], [146], [147]
	Decision Making	[10], [18], [33], [49], [77], [103], [119], [148], [149], [150], [151], [152], [153], [154], [155], [156]
	Asset Management	[23], [24], [76], [97], [104], [124], [145], [157], [158], [159], [160]

phases of road infrastructure: design, construction, and operation and maintenance. Table 6 summarized the distribution of semantic web technology adoption at different stages and their representative research. Of the 110 papers remaining after manual screening, those in the operation and maintenance stage accounted for the majority share, at 65 %. The clusters of "bridge maintenance", "intelligent bridge management", "infrastructure system" were mainly for different application scenarios during this stage. While the design and construction stages attracted relatively little research interest, with a similar proportion of 19 % and 16 %, respectively.

4.3.1. Design stage

The planning and design of road infrastructure was a task requiring cross-functional coordination. Ensuring seamless information transmission, exchange and integration between different participants was an effective solution to resolve temporal conflicts and redundant planning efforts. Semantic web technologies were driving innovation in the design stage of road infrastructure by enabling multi-disciplinary collaborative design and automated compliance checking (ACC), two rapidly evolving directions that addressed critical challenges in data interoperability and regulatory adherence. They defined the hierarchy and relationships of model elements, facilitating the integration and retrieval of information at both syntactic and semantic levels through mappings between different ontologies. For example, the IHP-Onto facilitated inter-temporal coordination among cross-functional highway agencies, improving cost-effective planning through integrated information sharing [38]. As BIM was constantly being developed as visually interactive platform with physical, geometric and attribute information of roads, bridges and tunnels [161] and taking into account the linear characteristics of these road infrastructures, the integration of GIS information with BIM model was also a pivotal issue to be addressed in the planning and design stage [162]. Zhao et al. constructed an IFC ontology to describe the hierarchies, attributes and relationships of BIM objects. They converted GIS data into OWL via an intermediate format, and mapped ontologies using graph matching for ontologies (GMO), enabling the integration of BIM and GIS data for highway route optimization [8]. Stepien et al. utilized an ontology database to integrate BIM and GIS at the data level, linking and evaluating information in a structured manner to create risk- and cost-optimized routes for mechanized excavation operations [123].

Additionally, ACC has garnered increasing attention in recent research. While studies on ACC in the building field, such as fire safety design verification [163], were relatively mature, research in the road infrastructure domain remained exploratory and limited to specific scenarios, primarily within the bridge field [126]. Semantic web technologies demonstrated significant potential in ACC by constructing domain-specific ontologies to encode design standards into machine-readable rule bases and employing logical reasoning tools (e.g., SWRL, SPARQL) to automate the verification of selected clauses. However, current ACC in road infrastructure domain still faced challenges such as simplified application scenarios, partial clause formalization (e.g., limited to quantifiable metrics), and weak semantic resolution of ambiguous clauses.

4.3.2. Construction stage

Semantic web technologies provided an innovative way to better support the construction management process for schedule management [164], safety management [17, 131, 132], and quality control [75, 128]. Ontologies developed for the construction stage should not only contain hierarchies and relationships representing construction model elements, but should also link the attribute information of instances in a logical manner, taking into account the specifications and the engineers' experiences [42]. For example, Koch et al. developed a tunnel information modeling framework in an open IFC environment to visualize settlement monitoring data and predict future conditions during tunnel construction [60], and Niknam et al. developed an ontology and created project knowledge base to effectively integrate schedule information with BIM for real-time information access and retrieval [164]. In construction safety management, based on semantic regulation checking, Fang et al. monitored workers' behavior for compliance with safety regulations and identified hazardous behaviors by constructing a hazard ontology model and combining it with computer vision algorithms [17]. Dong et al. proposed a knowledge-dynamics integrated map (KIM) to solve the safety knowledge visualization problem for workers with different professional qualifications and different educational backgrounds during the construction of tunnel projects [131] while Xu et al. defined SWRL rules for rollover risk assessment of engineering vehicles by semantic representation of rollover stability index and concepts correlation [132]. In addition, quality control played a crucial role in ensuring the high quality and long-term performance. Xu et al. proposed an ontological approach to manage construction quality inspection knowledge, which clarifies the content, timing and standard processes that need to be inspected by integrated with the construction business process [75]. Based on this, they further proposed an intelligent database approach that can automatically generate tailored lists of construction requirements according to user preferences which enhances the efficiency of construction quality inspection [128].

4.3.3. Operation and maintenance stage

The management of road infrastructure during its operational and maintenance phases primarily encompasses the inspection and assessment of technical conditions, decision-making for maintenance plans, and asset management. Scientific and effective management required the collaboration of massive heterogeneous data from multiple sources where semantic web technologies were widely accepted and highly anticipated.

In operational condition inspection and performance evaluation, semantic web technologies employed ontologies as a knowledge backbone to interlink the physical states of infrastructure with domain rules, enabling structured representation and integration of multidimensional knowledge. For instance, in bridge monitoring, the deterioration knowledge ontology (DT-KL-Onto) developed by Hu Xi et al. mapped bridge structural defects, defect attributes, and contributing factors into a computable semantic relationship network that enabled rule-based early warnings [47]. For tunnel health assessment, knowledge graph based on evolutionary characteristics dynamically correlated historical inspection data with degradation models, forming a semantic diagnostic framework for tunnel health monitoring [90]. In pavement performance analysis, semantic modeling frameworks combined with Bayesian networks clarified causal relationships between defects and factors like material aging and traffic loads, significantly enhancing the interpretability of degradation mechanisms [139]. These practices standardized ambiguous semantics in inspection reports and leveraged pretrained models like BERT to semantically parse unstructured text [141], significantly improving the interpretability of condition assessments and the explicit representation of domain rule-based knowledge.

In maintenance decision-making, semantic web technologies bridged the path from inspection data to domain knowledge and decision rules, transforming maintenance strategies from experience-driven to data-knowledge dual-driven paradigms. For instance, Yu et al. developed a tunnel digital twin system integrating ontologies and real-time sensor data to dynamically optimize preventive maintenance through semantic mappings and 3D simulations [10]. Hu et al. combined BIM, IFC, and semantic models to unify heterogeneous information and enhance lifecycle-based maintenance planning [151]. Additionally, ontology-driven systems such as PADTUN (pathology assessment and diagnosis of tunnels) demonstrated how semantic reasoning supports pathology diagnosis and decision-making in tunnel management by linking structured maintenance data repository with decision support system [142]. For bridges, Jiang et al. designed an ontology that semantically connects finite element analysis results with standard-based constraints, enabling optimal lifecycle multi-objective solutions [103]. Notably, cutting-edge research explored synergistic innovations between deep neural networks and semantic reasoning engines recent years, such as cascaded architectures integrating YOLOv8 defect detection models with knowledge graphs [153], or hybrid frameworks coupling finite element-based ML models with SWRL rule-driven knowledge repositories for bridge safety assessment [103]. Such innovations merged the perceptual capabilities of deep learning with the logic-driven rigor of semantic reasoning, significantly enhancing decision transparency and maintenance efficiency.

To meet digital transformation needs for life cycle asset management in road infrastructure domain, semantic web technologies constructed data exchange hubs across systems through domain ontology modeling. The European connected data for effective collaboration (CoDEC) project's BIM-AMS (asset management systems) integrated ontology broke semantic barriers between IFC standards and asset management systems, interlinks asset states, maintenance records, and resource scheduling data to enable lifecycle cost traceability and analysis [104]. Similarly, Hagedorn et al. introduced standardized information containers to connect road asset management systems or relational databases with BIM models, enabling cross-domain interoperability and federated queries of asset information [86]. Meanwhile, to address terminology inconsistencies, Le and Jeong adopted an NLP-based approach for automatic classification of semantic relationships among heterogeneous transportation asset data [124], while Mehrdad et al. modularized sub-ontologies to structurally reorganize cross-domain concepts (e.g., pavement inventory, performance degradation, economic costs) [76]. Furthermore, these NLP-driven semantic relationship classification algorithms [124] and dynamic data container technologies [86] enhanced the adaptive transformation of unstructured documents (e.g., maintenance logs, inspection reports) into knowledge graphs, significantly improving the scalability, accuracy, and actionability of asset management systems.

5. Limitations of Semantic Web Technologies for Road Infrastructure Applications

Section 4 demonstrated the substantial influence of the semantic web technologies on data exchange, semantic integration, knowledge management and decision support throughout the lifecycle of road infrastructures. Fig. 10 presented a preliminary framework for the applications of semantic web technologies in the field of road infrastructure, synthesizing the principal components and critical processes within this domain, which also responded to RQ3 in Section 1.

The integration of semantic web technologies in road infrastructure domain revolved around a four-layer collaborative mechanism encompassing requirements, data sets, knowledge, and decision-making. Among them, the development of ontology base and knowledge base played a fundamental role to the functioning of this system. The ontology base comprised interlinked core and domain ontologies, with the core ontology consisting of basic terms and relationships, while the domain ontology was tailored to a given specialty. Knowledge bases primarily hosted data containing semantic information such as concepts, facts, rules and relationships between these elements to support complex queries and reasoning, including knowledge representation based on description logic, using terminology box and assertional box describing domain structure and individual assertions respectively, as well as rule based explicitly representation of knowledge derived from regulations and domain experts.

The perspective of this system was that the participants, such as designers and managers, put forward the requirements and aims under various specialization backgrounds, and these task breakdowns can be aligned with the semantic information in the knowledge base, directly invoke existing ontologies or build new ones based on the core ontology to integrate cross domain data and knowledge, and also the associated rules in knowledge base can be selected and invoked through semantic matching. Comprehensive decision-making can then be achieved

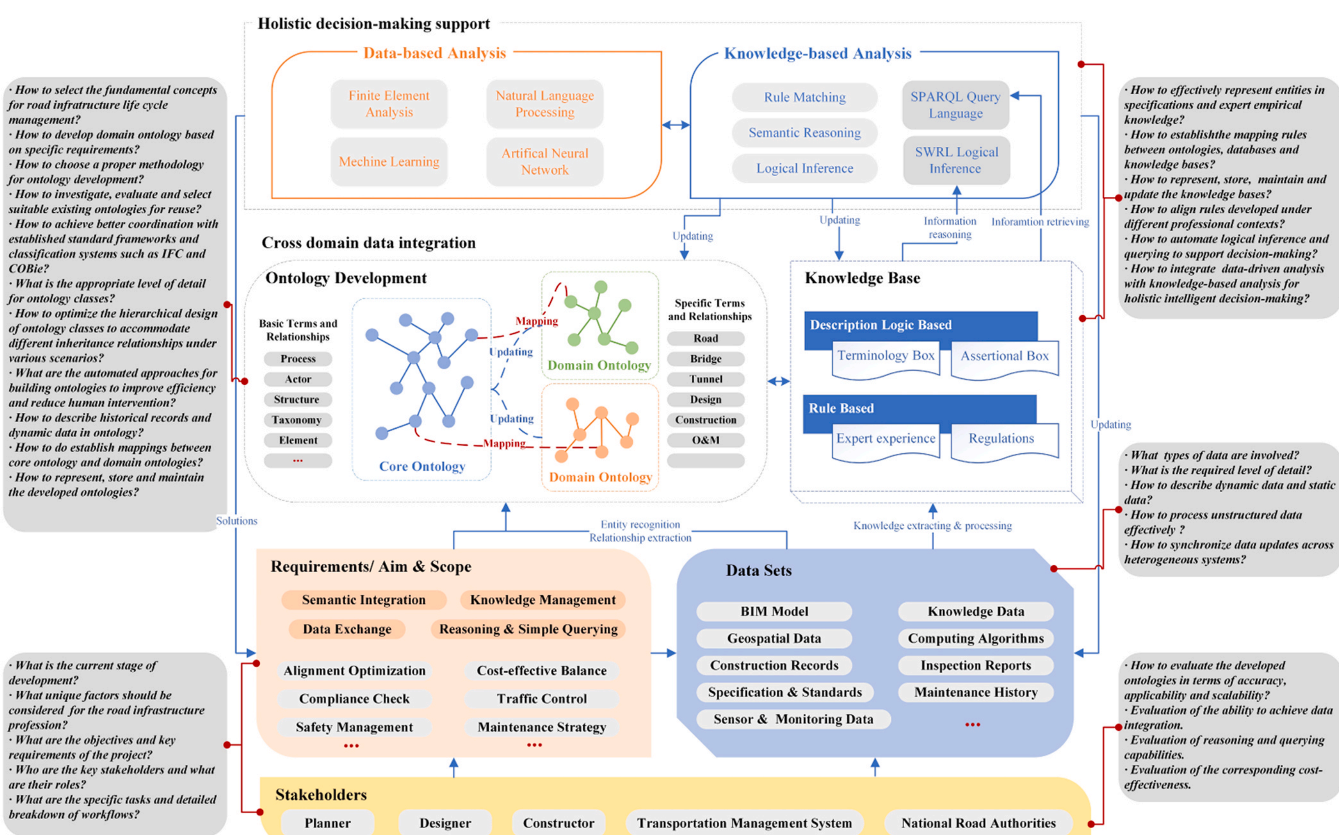

Fig. 10. A framework for the application of semantic web technologies in road infrastructure domain and issues to be considered.

through a combination of data-based analysis and knowledge-based analysis.

Nevertheless, there were still concerns that need to be considered and addressed throughout the whole process, including the breakdown of requirements and tasks, multi-source heterogeneous data acquisition and processing, ontology development methodologies, linking across domains, knowledge representation, and the collaboration between data-based and knowledge-based methods, and so on, as depicted in Fig. 10. These concerns were then collated from the following five aspects and the corresponding future improvements were further organized, which answered RQ4 in Section 1.

5.1. Lack of comprehensive guiding framework for semantic web applications in road infrastructure domain

Despite the construction of various semantic web application frameworks in several publications and case studies, there were still deficiencies in unification and reusability. Particularly, specific features essential for road infrastructure have not been given sufficient consideration. For instance, the large-span linear features and multidimensional spatial attributes of road infrastructure necessitate the handling of high-precision geometric parameters and spatial topological constraints during the design phase. The construction phase subsequently requires attention to component-level sequential data and resource scheduling logic, while the operation and maintenance phase demands seamless integration of real-time sensor data streams with historical degradation models. These three distinct lifecycle stages demonstrated divergent requirements regarding spatiotemporal granularity, attribute dimensionality, and dynamic characteristics of the data. Key challenges lie in balancing hierarchical data relationships across the entire life cycle, coordinating dynamic reconciliation mechanisms between static infrastructure data (e.g., BIM and GIS models) and dynamic real-time operational data (e.g., complex sensor detection data), ensuring consistency and precision in data description, updating, and processing, and supporting multi-granular scenarios ranging from route design and segment construction to preventive maintenance and emergency response. The current emphasis in the design and development of semantic web ontologies primarily prioritized data syntactic conversion over context-aware semantic translation, leading to redundancies in knowledge representation and inconsistencies in terminology [165]. Reducing redundancy while maintaining clarity and logical consistency, as well as fine-tuning hierarchical relationships in accordance with the data characteristics and requirements of various service phases of road infrastructure are matters should be taken into account.

In addition, current frameworks also lack scalable adoption pathways for emerging technologies such as digital twins, AI-driven anomaly detection, and multi-agent decision-making systems, limiting their applicability in complex scenarios like predictive maintenance or climate resilience planning. To address these barriers, a domain-specific comprehensive guiding framework is urgently needed to systematize ontology engineering, enforce semantic consistency, standardize knowledge management and bridge the gap between theoretical models and practical implementation. This framework should emphasize modular ontologies, automated logical inference, context-aware reasoning engines, and adaptive middleware to unify heterogeneous data sources, thereby unlocking the full potential of semantic web technologies in advancing intelligent, lifecycle-driven road infrastructure management.

5.2. Lack of specific ontology development protocols

The development of ontologies in the semantic web stack was the fundamental component for converting data from databases, BIM and GIS models, decision-making procedures, and other lifecycle asset data related to road infrastructure into machine-readable and interpretable information. As can be seen in Fig. 9, experts and scholars employed multiple methodologies for developing ontologies, which included Ontology Development 101, Methontology, NeOn, Uschold and Gruninger and others. Suitable procedures can be selected from these methodologies based on specific requirements. Among them, the establishment of ontology hierarchy and relationships involved diverse methods such as transformed into OWL files by referencing the IFC extension architecture [151, 159, 166, 167], converting from COBie's structural framework [119, 168], and defining the ontology structure and hierarchy from top-bottom, taking into account the practical application requirements and experts' experience [47, 49]. But occasionally different inheritance relationships might be involved for the same entity in different scenarios, which required a comprehensive and operational hierarchical design. In addition, despite the fact that the majority of the process for ontology development involved referencing published ontologies, especially as the application progresses, a large number of ontologies were created, giving rise to practical concerns such as inconsistent hierarchical structures that cannot be mapped and conflicting terms that result in ambiguity. A mechanism for investigating and evaluating existing ontologies was therefore needed, as well as screening guidelines to ensure the quality of ontologies while enhancing their reusability.

Moreover, in order to automate ontology development and minimize manual intervention, AI tools have recently being employed to identify and extract triples from historical document data for road monitoring, inspection, and operation and maintenance [51], but due to the continuous accumulation of data volume and the heterogeneity characteristics, there remained an inadequacy in research on how to extract information from not only textual documents but also multiple sourced structured and unstructured data. Further exploration was therefore required to delve deeper into this field. Meanwhile, the domain of road infrastructure encompassed not only the geometric and attribute data of the structural elements, but also the data on users, vehicles, climate conditions, and sensors during the operational phase, as well as data on computational models, decision-making procedures, and construction operations during the management process. It was impractical to develop a comprehensive ontology covering all of these knowledge domains, instead there were approaches through interlinked independent sub-domain ontologies [19, 77] or establishing a shared core ontology for other sub-domains to expand upon [27, 38]. Consequently, how the abstract concepts and relationships were selected for the development of the core ontology was one that required careful identification and multiple validations, and also for the creation and management of links between diverse sub-models, partial models and rule sets. Therefore, arriving at the optimal blueprint for developing ontologies that cater to varying fine-grained prerequisites for divergent business necessities and can facilitate cross-domain information retrieval and semantic reasoning at different stages presented a challenge that need to be deliberated thoroughly. Hence, it poses a task for academics and practitioners to devise a specific ontology development protocol that employs automated or semi-automated techniques to account for the data characteristics during road infrastructure life cycle and varying fine-grained needs for diverse business purposes while maintaining unambiguous terminologies and hierarchical structures.

5.3. Limited information integration and synchronization

Models such as BIM and GIS in the field of road infrastructure were mostly created in the design and construction stage, how to establish synchronous relationships between the massive existing data, especially road network data, geometric data, terrain data and computational models, and expanding the value of information to the whole life cycle of road infrastructure was a hot issue of current research concern. Experts and scholars endeavored to attain the synchronization of information through information containers [86], data wrappers [24], BIM and GIS cityGML ontology mapping rules [7], links between model elements and risk management [169], etc. Instead of achieving global interoperability, what was offered was a semantic-based data exchange that only synchronized and integrated elements between specific scenarios. Even if it was achievable to map original data structures to ontologies, beyond a certain point, a single ontology was unable to encompass all facets of the data model and lacked a thorough description of the application annotations of existing ontologies and interfaces with other ontologies [170]. Furthermore, taking into account the real-time characteristics of road information, there were issues relating to the temporal depiction of attributes and historical information overlay for instances when updating real-time data obtained from sensors. Future research should concentrate on how to accomplish full life cycle data integration and synchronization without altering the external database's structure or the current management system, which can access the external database's real-time updated data and also call upon the computational model and knowledge base of the system for management decisions in emergency situations and routine circumstances.

5.4. Insufficient automation of information extraction and alignment

To enhance the efficiency of information extraction and semantic alignment while reducing reliance on manual intervention, researchers have explored diverse automation strategies. This included tools such as initial mapping master plug-in for the ontology modeling tool protégé, designed to automatically convert spreadsheets into RDF triples [171], as well as hybrid machine learning systems integrating statistical models like CRF [51] and support vector machines (SVM) with feature engineering pipelines for entity-relation extraction [91]. With advancements in deep learning and large language models (LLMs), pre-trained language models like BERT have also been adopted for contextual named entity recognition and relationship extraction [107]. For semantic alignment, rule-based and logic-driven methods using predefined domain ontologies, mapping rules, and reasoning tools [49] have been actively investigated, alongside vector similarity calculations and relational reasoning techniques [92]. However, there was still insufficient automated conversion mechanism and manual mapping rule definition was still required.

For example, road infrastructure data predominantly resides in unstructured formats, necessitating labor-intensive customization of task-specific extraction rules with limited portability. Despite leveraging unsupervised learning in pre-trained language models, their training and fine-tuning processes still demand extensive annotated datasets. In downstream tasks such as named entity recognition and relationship extraction, current research remains constrained to predefined simple categories, offering limited functionality for handling nested entities, multi-level causal relationships, or composite event descriptions. Additionally, dynamic and multimodal semantic alignment faces compatibility challenges. While real-time sensor data requires dynamic logical updates to align with static ontologies, inference delays in rule engines often lead to adaptation lags. Joint reasoning across heterogeneous data sources was further complicated by coordinate system discrepancies and ambiguous terminology. Moreover, the increasing number of independently created ontologies catering to diverse business requirements, coupled with the exponential growth of networked data sources, has exacerbated domain ontology fragmentation and generalization costs. Differences in ontology definitions across systems and scenarios necessitate repetitive adjustments to annotation rules or knowledge model reconfiguration. Compounded by the absence of industry standards, terminological ambiguities, and low-quality noise data, significant manual intervention remains critical to ensure logical consistency.

To address these issues, future research should prioritize the standardization of core ontology bases for the road infrastructure, establishing consistent terminology and taxonomies across design, construction, and maintenance phases. This requires adaptive ontology development protocols to dynamically synchronize with real-time data streams while enabling multimodal joint embedding frameworks to resolve semantic conflicts. Domain-augmented hybrid learning systems should integrate LLMs with few-shot learning strategies, reducing reliance on annotated datasets, while semi-automated annotation tools can also lower labeling costs. Engineering standards and expert experiences can be embedded as symbolic constraints to ensure extraction precision and logical compliance. Concurrently, open collaborative platforms should foster cross-institutional ontology sharing, leveraging decentralized architectures to reconcile definitional ambiguities and streamline knowledge model updates. By converging these advancements, this field can shift toward scalable, low-intervention automation, where semantically unified, context-aware data integration can support proactive decision-making efficaciously.

5.5. Weak capacity of logical inference and decision support

Logical inference and reasoning were also significant considerations when deploying semantic web technologies for added value in the road infrastructure domain, where unknown facts or relationships can be inferred from existing facts or relationships in RDF and OWL using a common inference engine by simple DL principles. In most semantic web implementations, current research in the field of road infrastructure employed SWRL reasoning to build rule sets that were tailored to particular circumstances, such as mechanisms for identifying the operational status of tunnel equipment [119], keeping track of the condition of bridge structures and sending out early warnings [19], and performing compliance checks [105]. This was accomplished by specifying the prior (requirements that must be satisfied for the rule to be triggered), and as a consequent (actions that are executed after the rule is triggered). But the most of these rule bases followed a knowledge representation based on discrete symbols for reasoning, which had the benefits of strong logical constraints and high accuracy but the drawbacks of being difficult to scale and target-oriented, making it impractical to develop an exhaustive rule base for managing road infrastructure. Future research must look into ways to align rules developed by different domain experts as well as rules developed by the same domain expert over time or under various circumstances. Moreover, utilizing representation learning for reasoning in the mapped vector space is a novel technique that could be explored for adaptation to the road infrastructure management field. Furthermore, it was noteworthy that apart from algorithmic rules and mandatory requirements that take into account expert experience, industry standards and norms, an increasing amount of sensor data were taken into consideration to aid decision-making, particularly in the realm of the internet of things, where big data-driven methodologies were utilized in diverse areas like forecasting the deterioration of road and bridge performance and predicting the remaining lifespan of equipment. However, the data-based prognostication was hindered by factors such as the selection of variables, probabilistic models, and others, making the outcomes more unpredictable. How to integrate data-driven and knowledge-driven or theoretical model-driven methodologies for decision making throughout the entire life cycle of road infrastructure management, and to strengthen the deep cooperation between the road professional field and the computer industry need to be further explored and validated in the practical engineering environment in the future.

6. Conclusions

Semantic web technologies have demonstrated significant transformative potential in advancing the digital intelligence of road infrastructure domain, permeating all phases of its life cycle and evolving rapidly. To provide a comprehensive and up-to-date analysis and synthesis of research on semantic web technologies in this field, this study conducted a scientometric and clustering analysis of 141 selected papers to visualize the current status and trends of semantic web technology adoption in the road infrastructure industry. Through critical review, the achievements in practice and encountered obstacles were identified, offering insights to guide future research aimed at advancing intelligent management across the entire life cycle of road infrastructure.

Firstly, the analysis of publication-related information revealed fluctuating growth trends in research output, with two distinct peaks in 2016 and 2021. These peaks closely correspond to the transformative processes in engineering digitalization, namely the introduction of BIM and advancements in artificial intelligence. Meanwhile, a transition from conference papers to journal-dominated publications was observed, reflecting the field's maturation from exploratory methodologies to robust theoretical frameworks and practical validations. Geographically, research contributions were concentrated in China, United States, United Kingdom, Germany, and Australia. Notably, the Netherlands, despite contributing fewer studies, exhibited the highest betweenness centrality, underscoring its critical role in facilitating international collaboration. Co-authorship analysis identified influential research groups and highlighted emerging partnerships between engineering and computer science disciplines, though deeper interdisciplinary integration remains necessary. Document co-citation analysis emphasized seminal works that provided scientific definitions of ontologies and their development methodologies, early explorations of domain-specific ontologies, and integrations with AI methods.

Prominent research themes were identified through keyword analysis, such as BIM, digital twins, and deep learning, demonstrating semantic web technologies' abilities in bridging engineering semantics with machine-readable formats and enabling dynamic data-object-knowledge linkages within digital twins. Deep learning further enhanced the unstructured knowledge extraction and data-knowledge synergy for cross-domain scientific decision-making. Subsequently, clusters of these keywords were further analyzed through three dimensions: semantic web technologies analysis, the roles of semantic web technologies in the road infrastructure domain, and applications of semantic web technologies across the lifecycle of road infrastructure. A detailed examination of semantic web technologies included what they are and their core components, elaborated from perspectives such as term evolution path, ontologies and their development methodologies, description languages, and knowledge graphs. Three pivotal roles of semantic web technologies in the road infrastructure domain were then identified, namely data exchange and semantic integration, knowledge management, and reasoning and simple querying. From a lifecycle perspective, semantic web technologies spanned all stages of road infrastructure. However, their applications in the operation and maintenance phase dominated, leveraging semantic integration to enable condition monitoring, maintenance decision-making, and asset management. Innovations driven by these technologies in the design phase include multidisciplinary collaborative design and ACC, while in the construction phase, they offered novel solutions to enhance schedule management, safety management, and quality control.

Despite these advancements, critical challenges persist. Building on the above synthesis, this paper proposed a preliminary framework for semantic web applications in road infrastructure domain, synthesizing core components and key processes. Five major limitations in current applications were then identified: lack of comprehensive guiding framework for semantic web applications in road infrastructure domain; lack of specific ontology development protocols; limited information integration and synchronization; insufficient automation of information extraction and alignment; weak capacity of logical inference and decision support. To address these barriers, there is an urgent need for a road infrastructure domain-specific, integrated guiding framework to systematize ontology engineering, enhance semantic consistency, regulate knowledge management, leverage advanced AI tools, and bridge the gap between theoretical models and practical implementations, thereby unlocking the full potential of semantic web technologies in advancing intelligent road infrastructure life cycle management.

Finally, while this study offered an in-depth review of the applications of semantic web technologies in road infrastructure domain, certain limitations must be acknowledged. Firstly, the literature review emphasized influential journal articles and conference papers, yet practical case studies from real world applications were underrepresented. As research materials continue to accumulate, future efforts should actively integrate empirical insights from these cases to enhance theoretical frameworks and address practical challenges. Secondly, while the adoption and investigation of semantic web technologies in road infrastructure exhibit domain-specific characteristics, they share fundamental logic and research paradigms with the AEC domain. Although we drew insights from research frameworks in this domain during our analysis, comparative exploration was not conducted deeply. Future work should involve a thorough comparison and synthesis of the application priorities between these two fields to identify tailored development pathways for the road infrastructure domain.

CRediT authorship contribution statement

Xinhua Mao: Writing – review & editing, Software, Resources, Methodology, Funding acquisition. **Jianwei Wang:** Supervision, Project administration, Funding acquisition, Conceptualization. **Rujie Zhang:** Writing – original draft, Investigation, Formal analysis, Data curation. **Haijiang Li:** Writing – review & editing, Resources, Methodology, Conceptualization.

Declaration of Competing Interest

The authors have declared no conflict of interest.

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