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Semantic interoperability in IoT for Industry 4.0: Review, taxonomy, challenges, and future research

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ABSTRACT

Semantic interoperability is a critical enabler for achieving the Industry 4.0 vision, ensuring that heterogeneous IoT devices, systems, and applications can exchange and interpret data consistently. Despite its importance, achieving semantic interoperability continues to pose significant challenges due to the diversity of data formats, standards, and ontologies used across industrial IoT environments. This paper presents a comprehensive review and taxonomy of semantic interoperability within Industry 4.0, analyzing existing frameworks, protocols, and ontological models. We classify current approaches based on their architectural layers, semantic technologies, and application domains. Additionally, this study identifies the limitations of prevailing solutions, highlights open research challenges, and proposes future directions for enhancing semantic interoperability in industrial IoT systems. The insights provided aim to support researchers and practitioners in developing scalable, secure, and semantically aligned IoT ecosystems for Industry 4.0.

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1. INTRODUCTION

The IoT refers to a rapidly expanding ecosystem of interconnected physical objects ranging from vehicles and home appliances to industrial machinery which are embedded with electronics, software, sensors, and network connectivity, enabling autonomous data collection, exchange, and processing [1]. This integration of the physical and digital worlds has driven transformative changes across sectors such as manufacturing, healthcare, transportation, and smart cities, improving operational efficiency, decision-making accuracy, and economic productivity.

The emergence of Industry 4.0 has further accelerated the deployment of IoT, by merging cyber-physical systems (CPS) with intelligent industrial infrastructures to enable autonomous, real-time, and adaptive production environments [2]. Central to the success of Industry 4.0 is the seamless interchange, comprehension, and utilization of data generated by heterogeneous IoT devices, platforms, and services. A major barrier to achieving this vision is the lack of semantic interoperability, which ensures that devices and systems from diverse manufacturers interpret and process exchanged data with a consistent, shared understanding [3]. Without this capability, Industry 4.0 infrastructures struggle to integrate new devices and services efficiently and manage data-driven decision-making workflows reliably.

The global IoT landscape continues to expand at a remarkable pace, with recent projections estimating that over 75 billion IoT devices will be operational by 2026 [4]. This exponential growth is fueled by the growing demand for smart homes, industrial automation, connected vehicles, and wearable technology [5], [6]. Consequently, the volume of data generated by IoT systems is anticipated to surpass 175 zettabytes annually by 2025, presenting unprecedented challenges in terms of data storage, real-time processing, integration, and analysis [7], [8].

A primary obstacle lies in the significant heterogeneity of IoT devices, which vary widely in terms of their hardware capabilities, communication protocols, data formats, ontological models, and security architectures [9], [10]. This heterogeneity contributes to fragmented IoT ecosystems, data silos, and interoperability bottlenecks, undermining the scalability, adaptability, and reliability of Industry 4.0 infrastructures. The problem is further compounded by the accelerated pace of digital transformation catalyzed by the COVID-19 pandemic, which highlighted the urgent need for interoperable, resilient, and scalable IoT architectures capable of supporting autonomous and distributed industrial operations [11], [12].

Recent studies have explored various semantic interoperability frameworks, ontological models, and middleware solutions that aim to harmonize data semantics across heterogeneous IoT environments [10]. Notably, Multidisciplinary Digital Publishing Institute (MDPI) research has proposed a metamodeling-based interoperability and integration testing platform that formalizes IoT system interactions and enables cross-platform validation across diverse devices and data flows [13]. This work demonstrates the feasibility of systematic interoperability management approaches but highlights ongoing limitations in dynamic semantic alignment and real-time integration for large-scale industrial deployments.

Moreover, research in applied domains has emphasized the practical advantages of semantic interoperability. For instance, a spatio-temporal semantic data management framework has been deployed in precision agriculture to enhance interoperability in IoT-driven farming environments [14]. Similarly, an ontology-based semantic middleware for smart campus infrastructures has demonstrated the ability to automate device and data integration workflows in heterogeneous IoT systems [15]. These implementations reinforce the importance of semantically aware architectures, though universal, scalable, and domain-independent solutions remain elusive.

Despite these advancements, achieving seamless, scalable, and dynamic semantic interoperability in IoT systems for Industry 4.0 remains an open research challenge. The absence of universally adopted semantic frameworks and the limited maturity of real-time semantic alignment mechanisms continue to hinder the integration of heterogeneous devices, platforms, and services [15].

To address these challenges, this paper presents a comprehensive review and taxonomy of semantic interoperability frameworks, ontologies, and enabling technologies for IoT in Industry 4.0. It categorizes existing approaches based on their architectural layers, semantic models, and application domains; identifies persistent limitations and open research challenges; and proposes future research directions to guide the development of scalable, dynamic, and domain-independent semantic interoperability solutions for industrial IoT ecosystems.

Semantic interoperability has become a critical research topic within the industrial IoT domain, gaining increasing attention due to its role in enabling seamless data exchange and system integration in Industry 4.0 environments. Numerous studies have investigated various approaches to achieving semantic interoperability however, several open challenges remain.

To understand the current state of the art, identify existing gaps, and propose future directions, this paper conducts a comprehensive review of recent research on semantic interoperability in IoT for Industry 4.0. In particular, the following research questions (RQs) guide the scope and objectives of this study:

- RQ1: How is semantic interoperability defined in the context of Industry 4.0 and industrial IoT?
- RQ2: What approaches and strategies have been proposed in previous studies to address semantic interoperability in IoT, and how effective are they?
- RQ3: What are the primary challenges and limitations faced by IoT systems and Industry 4.0 infrastructures due to the lack of semantic interoperability?
- RQ4: What future research directions and open challenges need to be addressed to enhance semantic interoperability in IoT systems for Industry 4.0?

To address these research questions, the remainder of this paper is organized as follows: Section 2 provides an overview of interoperability components within IoT systems. Section 3 and section 4 discuss semantic interoperability technologies and the key obstacles to achieving semantic interoperability, respectively. Section 5 outlines the operational and integration challenges caused by the lack of semantic interoperability in IoT environments. A comprehensive review of related works is presented in section 6. Finally, the paper concludes with a summary of key findings, current limitations, and proposed future research directions in section 7.

This paper aims to provide a comprehensive analysis of semantic interoperability in IoT systems within the context of Industry 4.0. It reviews the current state of interoperability technologies, highlights the challenges posed by semantic heterogeneity, and identifies open research problems that hinder seamless data exchange and integration in industrial IoT environments.

The main contributions of this study are summarized as follows,

- To define and clarify key concepts related to IoT interoperability, including semantic interoperability, semantic technologies, and their underlying models and frameworks.
- To systematically review and categorize existing semantic interoperability processing strategies based on recent research contributions.
- To identify and analyze the major challenges and limitations faced by IoT and Industry 4.0 systems due to insufficient semantic interoperability.
- To discuss open research challenges and future research directions for enhancing semantic interoperability in IoT-based Industry 4.0 ecosystems.

2. RESEARCH METHOD

This study employs a semi-systematic literature review methodology to investigate semantic interoperability within the context of Industry 4.0 and the IoT. A semi-systematic review is appropriate for conceptually broad and emerging fields where research outcomes are heterogeneous and quantitative data may be limited [16]. This approach aims to identify, analyze, and synthesize conceptually significant patterns within the existing literature through meta-narrative synthesis. It was chosen for this research as it enables a concise, contextually relevant, and critical overview of the state of knowledge on semantic interoperability in IoT for Industry 4.0.

The review process follows the six-step framework proposed by Templier and Pare, which includes the formulation of research questions, literature search, study screening, quality appraisal, data extraction, and synthesis as illustrated in Figure 1 [17]. The research questions (RQ1–RQ4) were designed to explore definitions, existing approaches, challenges, and future directions related to semantic interoperability. In the second phase, a comprehensive literature search was conducted across multiple academic databases including Scopus, Web of Science, ScienceDirect, DOAJ, and Google Scholar. Keywords such as “semantic interoperability,” “IoT,” “Industry 4.0,” “ontology,” and “semantic frameworks” were used in various combinations with Boolean operators to refine the search results. Both published and unpublished articles were considered to capture a comprehensive picture of the current research landscape. Additionally, interoperability-related concepts in adjacent areas, such as fog computing and industrial automation, were also explored to contextualize the findings.

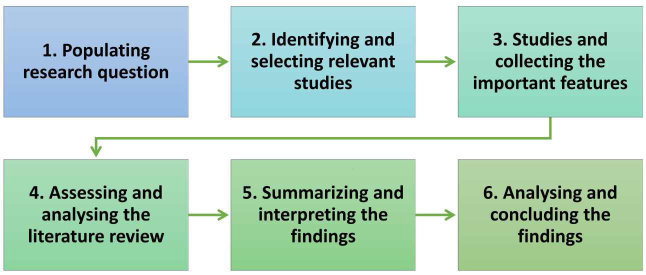

Figure 1. Implemented research methodology steps

During the third phase, a screening procedure was implemented based on predefined inclusion criteria, such as selected studies be published between 2015 and 2024 and relevance to interoperability definitions, conceptual models, technological frameworks, and application contexts within industrial IoT systems. Studies were excluded if they were non-English, lacked relevance to semantic aspects, or were duplicates. Studies were initially screened by title and abstract, followed by full-text screening. The fourth phase involved a quality appraisal of the selected studies, assessing their research design, methodology, and findings for academic rigor and relevance.

In the fifth phase, data extraction was conducted on the finalized set of studies. Key information such as definitions, models, interoperability dimensions, technologies, and challenges was systematically recorded. This process identified the foundational elements of semantic interoperability relevant to IoT and Industry 4.0.

The final phase involved data analysis and synthesis through content analysis techniques commonly applied in narrative reviews [16]. This facilitated the identification of themes, trends, and challenges in the literature, forming the basis for the taxonomy, challenges, and future research directions proposed in this paper.The final dataset included 70 peer-reviewed articles, with emphasis on recent contributions from 2020 to 2024. These studies span multiple domains including smart manufacturing, healthcare, smart cities, and industrial automation, ensuring broad coverage of semantic interoperability challenges and solutions.

While the semi-systematic approach provides a rich conceptual overview, it may not capture all quantitative metrics or unpublished industrial implementations. Additionally, the reliance on English-language sources may exclude relevant regional studies. Despite these limitations, the methodology offers a robust foundation for understanding the current landscape and guiding future research in semantic interoperability for Industry 4.0.

3. RESULTS AND DISCUSSION

3.1. IoT interoperability

This section addresses the first research question by providing an overview of interoperability within the IoT ecosystem, particularly in the context of Industry 4.0. In IoT systems, interoperability refers to the ability of heterogeneous devices, platforms, and applications developed by different manufacturers or vendors to seamlessly communicate, exchange, and utilize data within a unified environment [18]. It ensures that devices operating on distinct hardware architectures, software protocols, and communication standards can effectively collaborate and deliver integrated services [19], [20].

Achieving interoperability in industrial IoT systems requires the adoption of standardized communication protocols, data formats, and integration frameworks [21]. Common lightweight communication protocols such as message queuing telemetry transport (MQTT), constrained application protocol (CoAP), and HTTP are widely employed to enable reliable data exchange among resource-constrained IoT devices [22]. Similarly, standardized data serialization formats like JSON, XML, and YAML facilitate syntactic compatibility and simplify data processing across disparate systems [23].

Beyond device-to-device communication, interoperability also extends to the integration of diverse subsystems, including edge devices, cloud platforms, data analytics tools, and enterprise applications [10]. This necessitates the use of integration frameworks, middleware, and standardized APIs that allow seamless data exchange and operational coordination across heterogeneous infrastructures. Interoperability is essential for realizing the full potential of IoT-based Industry 4.0 environments, as it enables diverse systems to cooperate and deliver cohesive, scalable, and adaptive industrial solutions. Figure 2 illustrates these four fundamental dimensions of interoperability in IoT systems, highlighting the relationships and integration requirements among them.

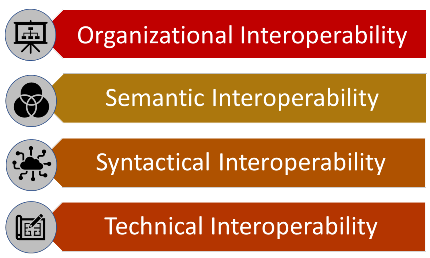

Figure 2. The dimensions of interoperability [24]

Interoperability within the IoT context encompasses multiple dimensions, each addressing a distinct aspect of integration. According to Santos *et al.* [25], these include technical, syntactic, semantic, and organizational interoperability. A clear understanding of these interoperability types is crucial for the effective implementation and management of interoperable IoT systems. The four primary dimensions are summarized as follows,

- Technical Interoperability: The ability of devices, systems, and applications to communicate and exchange data using common networking protocols, communication standards, and data serialization formats. It establishes the foundational connectivity necessary for device-level integration in IoT environments [26].
- Syntactic Interoperability: The capacity of disparate systems to exchange data in a structured and recognizable format, ensuring that the transmitted data can be correctly parsed and understood by receiving systems. This is typically achieved through standardized data formats such as JSON, XML, and RDF [27].
- Semantic Interoperability: The ability of systems and applications to interpret the meaning of exchanged data consistently and meaningfully. Semantic interoperability ensures that data semantics are preserved across heterogeneous systems, enabling accurate and context-aware information exchange [28].
- Organizational Interoperability: The capability of different organizations, business processes, and governance structures to effectively collaborate and exchange information across IoT systems, supported by compatible policies, standards, and business objectives [29].

In summary, achieving comprehensive interoperability across these dimensions is crucial for ensuring the seamless integration and efficient operation of industrial IoT systems. It enables diverse devices, platforms, and organizations to cooperate in real time, facilitating scalable, intelligent, and automated Industry 4.0 environments. The subsequent section will specifically examine semantic interoperability, its technological enablers, and its pivotal role in overcoming integration barriers within IoT-based industrial systems.

3.2. Taxonomy of semantic interoperability in IoT for Industry 4.0

Semantic interoperability is a crucial component in Industry 4.0 IoT ecosystems, as it ensures that devices, systems, and applications can exchange, interpret, and process data with a shared, unambiguous understanding of its meaning [30]. It enables heterogeneous devices to interact autonomously and allows applications to leverage data from diverse sources without ambiguity or the need for human intervention [28], [31], [32]. Importantly, semantic interoperability extends beyond merely defining information models or aligning data transport formats; it involves the consistent and meaningful interpretation of exchanged data across distributed systems and knowledge frameworks.

In recent years, significant advancements have emerged in semantic technologies tailored for Industry 4.0 and related domains such as healthcare and smart cities [33]-[35]. For example, Elkhodr *et al.* [36] proposed a blockchain-integrated semantic IoT middleware that leverages ontology-powered context awareness and secure data exchange, addressing both semantic alignment and trust in healthcare IoT deployments. Additionally, NGSI-LD an ETSI-standardized information model and API has been widely adopted across smart industry and digital twin projects, enabling contextualized semantic data interchange between platforms [37].

Among widely adopted standards is the semantic sensor network (SSN) ontology, which provides a formal, machine-interpretable framework for describing sensors, observations, and related metadata [38]. Likewise, the open platform communications unified architecture (OPC UA) has been recognized as a key Industry 4.0 standard, offering a unified data model and service set for seamless, platform-independent data exchange across industrial systems [39]. These efforts highlight the importance of semantic ontologies in enabling standardized and scalable industrial data ecosystems.

Given the complexity and diversity of industrial environments, achieving semantic interoperability requires a multidimensional approach that considers various architectural, technological, and modeling aspects [40]. To systematically analyze the current landscape and guide future research, a taxonomy comprising five key dimensions proposed in this section: network model, ontology, middleware, data model, and information model. These dimensions, as illustrated in Figure 3, were derived from a synthesis of recent literature and reflect the most influential factors shaping semantic interoperability frameworks in Industry 4.0 [41].

The network model dimension categorizes semantic interoperability solutions based on their deployment architecture. Fog-based models perform semantic processing at the edge of the network, closer to data sources [42]. These models are particularly suited for latency-sensitive applications, such as real-time monitoring and control in industrial automation, as they offer reduced data transmission delays and improved responsiveness [43]. Cloud-based models centralize semantic operations in cloud infrastructures, benefiting from scalable computing resources and supporting large-scale data aggregation and reasoning tasks [43]. However, they may introduce latency and bandwidth overhead, making them less suitable for time-critical applications. Web-based models leverage web technologies and standards to enable semantic data exchange across distributed systems, offering advantages for interoperability across organizational boundaries and integration with external services [44].

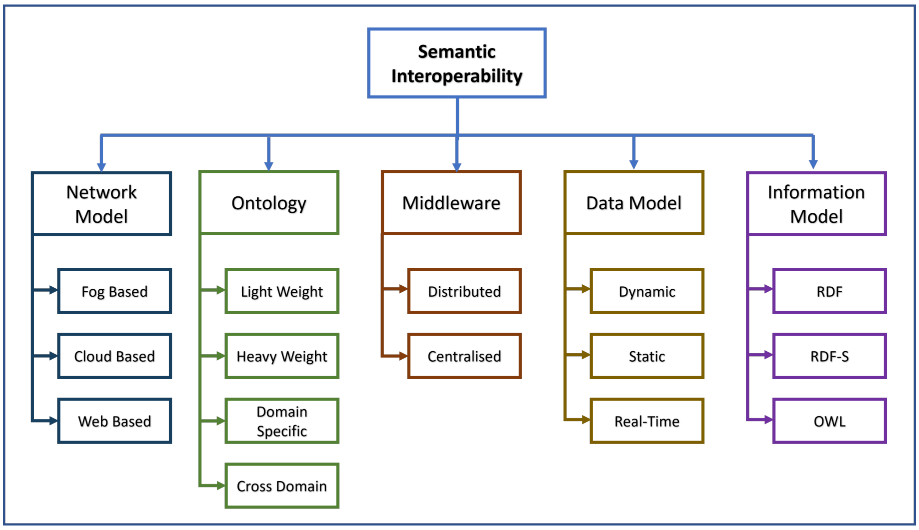

Figure 3. Taxonomy of semantic interoperability [24]

Ontologies serve as the backbone of semantic interoperability by providing formal representations of domain knowledge [45]. The taxonomy distinguishes between lightweight, heavyweight, and domain-specific ontologies. Lightweight ontologies are designed for simplicity and efficiency, making them suitable for resource-constrained devices such as sensors and embedded systems [45]. Heavyweight ontologies offer rich semantic expressiveness and support complex reasoning, typically used in centralized systems or cloud environments where computational resources are abundant [46]. Domain-specific ontologies are tailored to particular industrial sectors, such as manufacturing or healthcare, capturing specialized terminology and relationships that enhance semantic precision and contextual relevance. This classification reflects the trade-off between semantic richness and system performance, where lightweight ontologies enable fast processing but may lack depth, while heavyweight and domain-specific ontologies provide detailed semantic coverage at the cost of increased complexity.

Middleware plays a pivotal role in managing communication and semantic integration between diverse IoT components [47]. The taxonomy includes distributed and centralized middleware architectures. Distributed middleware decentralizes semantic services across multiple nodes, enhancing scalability, fault tolerance, and flexibility, which is particularly suitable for large and dynamic industrial environments [48]. Centralized middleware consolidates semantic processing in a single location, simplifying management and deployment but potentially limiting scalability and resilience [49]. The distinction between these architectures is based on design choices that directly impact system performance, maintainability, and adaptability [48]. Distributed middleware is increasingly favored in Industry 4.0 due to its alignment with decentralized and autonomous system requirements.

The data model dimension addresses how semantic data is structured and managed within IoT systems. It includes dynamic, static, and real-time models. Dynamic models support schema evolution and accommodate changes in data structures over time, essential for environments where devices and services are frequently updated or reconfigured [50]. Static models rely on fixed schemas and predefined data structures, offering simplicity but limited flexibility [15]. Real-time models enable immediate semantic interpretation of streaming data, which is critical for time-sensitive applications such as predictive maintenance and real-time analytics [15]. This classification is justified by the need to balance flexibility, performance, and complexity in data handling, with dynamic and real-time models being particularly relevant for Industry 4.0 [51].

Information models define the formal languages and standards used to represent semantic data. The taxonomy includes resource description framework (RDF), RDF schema (RDF-S), and web ontology language (OWL) [52]. RDF provides a foundational model for representing information about resources in the semantic web. RDF-S extends RDF by offering basic constructs for describing groups of related resources and their properties [52]. OWL offers advanced capabilities for defining and reasoning over complex ontologies, supporting higher levels of semantic expressiveness [53]. These standards are widely adopted in semantic web technologies and provide the syntactic and semantic foundation for interoperability. The classification reflects the progression from basic data representation to more advanced semantic modeling and reasoning capabilities, allowing systems to choose the appropriate level of expressiveness based on their requirements [53].

The taxonomy presented in Figure 3 offers a comprehensive framework for understanding the structural and functional components of semantic interoperability in Industry 4.0. Each classification dimension was selected based on its prevalence in the literature and its practical relevance to industrial IoT deployments. By organizing the landscape into these five categories, the taxonomy facilitates comparative analysis, highlights existing gaps, and supports the development of robust, scalable, and adaptive semantic interoperability solutions.

In addition to these, advanced semantic technologies, such as artificial intelligence (AI), machine learning, and natural language processing (NLP) have gained traction for automating data mapping, ontology alignment, and semantic annotation processes in IoT environments [54], [55]. For instance, Linardatos *et al.* [56] applied machine learning to automate the classification of sensor data from heterogeneous sources, improving semantic alignment and enhancing interoperability in Industry 4.0 contexts. Another recent study proposed a framework for automatically detecting and classifying data streams within manufacturing processes to improve operational efficiency and semantic integration in production systems [57].

Cross-platform and cross-domain interoperability are equally vital for Industrial IoT applications, particularly in scenarios requiring data exchange between independent systems or organizations [58]. Further efforts have introduced technologies and tools for enhancing cross-domain semantic interoperability. For example, Abburu [59] proposed a method for integrating multi-source IoT data by combining ontologies with machine learning techniques for automated data mapping and conversion. Similarly, Davies and Fisher [60] demonstrated how embedded semantic models and annotations within industrial applications improve IoT data consistency, scalability, and operational efficiency. Balakrishna *et al.* [61] highlighted the importance of semantic models for optimizing industrial IoT applications' scalability and sustainability in Industry 4.0.

Despite these advancements, seamless, scalable, and dynamic semantic interoperability remains an open research challenge. As recent studies emphasize, the lack of universally adopted semantic frameworks and the limited maturity of real-time semantic alignment mechanisms continue to hinder the full integration of heterogeneous devices, platforms, and services in high-frequency, data-intensive Industry 4.0 environments [62]. Ongoing research into semantic data annotation, reasoning, discovery, and visualization is critical to addressing these barriers and enabling truly autonomous, interoperable industrial ecosystems.

3.3. Obstacles to achieve semantic interoperability in Industry 4.0

Achieving semantic interoperability in Industry 4.0 IoT environments presents several persistent challenges due to the sheer diversity of devices, communication protocols, data formats, and operational contexts [59]. Numerous studies have identified critical obstacles that hinder seamless semantic interoperability in heterogeneous industrial systems [63]-[65].

One of the primary challenges lies in the incompatibility of communication protocols and data formats across devices and platforms. Although standardized protocols such as MQTT, CoAP, and OPC UA have gained traction, the lack of universally accepted semantic data models and ontologies limits interoperability and impedes cross-platform integration [41], [66]. Consequently, data generated by diverse IoT devices often remains confined within isolated silos, complicating data aggregation, semantic alignment, and real-time analytics in Industry 4.0 environments [67].

Device heterogeneity represents another significant barrier, as industrial IoT systems typically comprise devices from multiple manufacturers, each employing distinct data models, terminologies, and contextual interpretations [68]. This inconsistency in semantic structures leads to difficulties in achieving a common understanding of exchanged data, thereby affecting system interoperability and integration at the semantic layer.

The scale and variety of data produced by IoT devices in Industry 4.0 applications further exacerbate interoperability challenges. The enormous volume of heterogeneous, real-time, and unstructured data demands efficient semantic data modeling, knowledge management, and integration techniques capable of supporting dynamic, scalable, and context-aware interoperability solutions [69], [70].

Privacy and security concerns also constitute critical obstacles to semantic interoperability. Industrial IoT systems frequently handle sensitive operational, organizational, and personal data, necessitating robust privacy-preserving mechanisms and secure semantic data exchange protocols [71]. Without adequate security models and access control mechanisms integrated into semantic interoperability frameworks, data confidentiality, integrity, and trust cannot be ensured in interconnected industrial ecosystems.

To address these challenges, a range of approaches have been proposed, including the adoption of ontology-based frameworks, semantic web technologies, and machine learning-assisted semantic mapping techniques [32], [69], [72], [73]. These solutions aim to enhance semantic compatibility among heterogeneous platforms, automate data mapping and translation processes, and establish common knowledge representation frameworks to facilitate seamless data exchange, integration, and reasoning within Industry 4.0 environments.

In summary, while notable progress has been made in developing semantic interoperability frameworks and tools, achieving scalable, secure, and dynamic semantic integration across heterogeneous industrial IoT systems remains an unresolved research challenge. Addressing these barriers requires the continued advancement of ontology engineering, real-time semantic annotation techniques, and AI-driven interoperability solutions tailored to the demands of Industry 4.0.

3.4. Challenges caused by shortcomings of semantic interoperability in IoT for Industry 4.0

Several operational and strategic challenges within Industry 4.0 IoT ecosystems have been identified as direct consequences of insufficient semantic interoperability [74]. These shortcomings hinder the scalability, efficiency, accessibility, and economic viability of industrial IoT deployments. The principal challenges are outlined as follows:

- Restricted scalability, The integration of new IoT systems, devices, and applications at scale is significantly constrained when semantic interoperability is lacking [75]. The absence of standardized semantic frameworks leads to compatibility issues, making it difficult to incorporate advanced or heterogeneous devices into existing systems without extensive custom integration efforts [68]. This limitation ultimately restricts the scalability and flexibility of Industry 4.0 infrastructures.
- Inefficient data storage and resource utilization: Industrial IoT systems generate vast volumes of heterogeneous data from distributed devices. Without adequate semantic interoperability, effective data sharing across applications and platforms becomes difficult, resulting in redundant or siloed storage of overlapping data [66]. This inefficiency increases storage costs and complicates large-scale data management in Industry 4.0 environments.
- Vendor lock-in: A lack of semantic interoperability forces industries to adopt proprietary IoT systems and devices from single vendors, as integration with alternative systems is often complex and costly [58]. This vendor dependency restricts system flexibility, hinders the adoption of competitive technologies, and impedes long-term innovation by creating monopolistic tendencies within the industrial IoT market.
- Reduced system accessibility and Data Sharing: Interoperability limitations result in closed, siloed IoT ecosystems where data and services cannot be easily accessed or shared across platforms and applications [76]. This restricted accessibility diminishes the potential for integrated, cross-organizational collaboration, limiting the operational and strategic benefits of Industry 4.0 architectures.
- Technological uncertainty and instability: The absence of unified semantic interoperability frameworks increases the risk of technological fragmentation, where vendors fail to deliver agreed-upon services or maintain consistent functionality across devices [77]. Industrial operators are then forced to adopt unreliable or unstable solutions due to incompatibility constraints, undermining operational continuity and trust in IoT systems.
- Increased operational costs: The cost of deploying and maintaining Industry 4.0 IoT ecosystems escalates in the absence of semantic interoperability [65]. Industries are frequently unable to adopt more affordable, advanced IoT solutions without fully replacing existing incompatible systems. This lack of modular upgradeability drives higher operational expenses and reduces the economic feasibility of long-term IoT deployments.

In summary, semantic interoperability deficiencies introduce substantial barriers to the scalability, efficiency, and cost-effectiveness of Industry 4.0 IoT systems. Addressing these challenges is essential for enabling flexible, scalable, and integrated industrial ecosystems capable of supporting dynamic, data-driven operations. The following sections review current solutions and propose future research directions for overcoming these limitations.

3.5. Recent research efforts toward achieving semantic interoperability

Semantic interoperability has emerged as a crucial component of IoT frameworks for Industry 4.0 applications [78]. Various studies and research projects have proposed frameworks, ontologies, and distributed architectures to address semantic interoperability challenges within heterogeneous IoT ecosystems [20], [61].

Ontology-based models, fog computing-assisted semantic architectures, and lightweight semantic frameworks are among the widely explored approaches.

Iong and Smys [79] proposed a fog-assisted semantic framework designed to enhance interoperability among IoT devices by integrating fog computing principles with semantic technologies. The framework introduces a distributed computing infrastructure where fog nodes perform localized data aggregation, filtering, modeling, and semantic annotation before forwarding processed data to cloud servers for archival and advanced analytics in Figure 4. The semantic model within this framework utilizes standardized representations based on semantic web technologies such as RDF and OWL, facilitating seamless data exchange and interoperability across heterogeneous devices. Additionally, Iong and Smys proposed data prioritization algorithms within the fog layer to optimize data transmission efficiency and reduce service delays, thereby supporting scalable, interoperable Industry 4.0 systems.

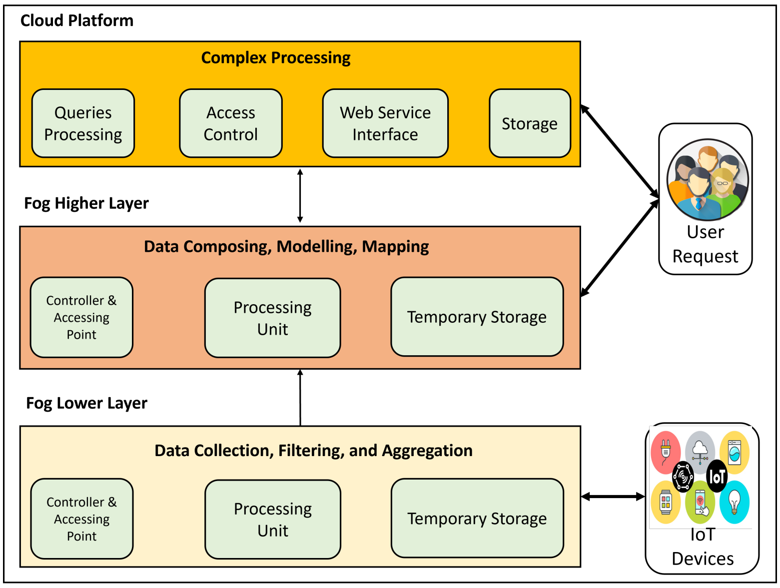

Figure 4. Fog-assisted semantic framework

Rahman and Hussain [80] introduced a lightweight ontology model (LiO-IoT) to support semantic interoperability for commonly encountered IoT components such as sensors, actuators, and radio frequency identification (RFID) systems. The ontology focuses on minimizing complexity by adopting a simplified semantic representation, improving processing efficiency in constrained IoT environments. However, the proposed model lacks dynamic semantic adaptability, a limitation subsequently addressed in Rahman's later work [73], which introduced a lightweight dynamic ontology framework. This dynamic ontology integrates machine learning techniques for automatically identifying and incorporating new attributes and concepts into the ontology, facilitating real-time semantic adaptation. The framework employs clustering algorithms to detect novel patterns within data streams, though the authors acknowledged that clustering-induced delays may impact system response times in time-sensitive industrial applications.

Further extending semantic interoperability solutions, Rahman and Hussain [81] proposed a fog-based semantic framework that migrates semantic processing tasks traditionally handled at the cloud level to distributed fog nodes. This hierarchical fog computing architecture consists of Level-2 (L2-Fog) nodes responsible for initial data collection, filtering, and aggregation, and Level-1 (L1-Fog) nodes tasked with higher-level semantic modeling, annotation, and decision-making in Figure 5. Semantic annotation is achieved using lightweight OWL-based ontologies managed via a lightweight middleware layer. By shifting semantic reasoning and data processing closer to data sources, this framework reduces network utilization, energy consumption, and service latency while improving interoperability across heterogeneous IoT devices. However, the framework relies on static ontologies, limiting its ability to dynamically accommodate emerging devices or evolving semantic contexts.

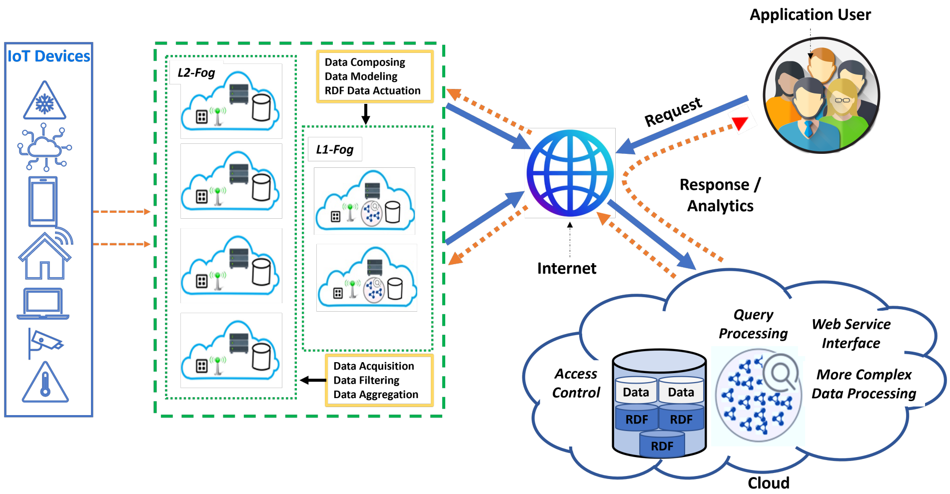

Figure 5. The framework of the suggested model

Gyrard and Serrano [82] proposed a unified semantic engine for IoT and smart city applications that integrates semantic web technologies, big data analytics, and IoT middleware. The engine comprises three layers: a data layer for collecting and preprocessing sensor data, a semantic layer for standardizing and annotating data using ontologies, and an application layer for developing context-aware services. The authors validated their approach through a smart parking use case, demonstrating the engine's ability to process and analyze real-time sensor data, enabling intelligent parking management decisions. Although focused on smart city deployments, the engine's scalable, ontology-driven architecture offers valuable insights for Industry 4.0 semantic interoperability frameworks.

Collectively, these studies highlight the diverse methodologies proposed to address semantic interoperability challenges in industrial IoT environments. Table 1 shows the capabilities and limitation analysis of the related work discussed. Although ontology-based models, fog-assisted frameworks, and lightweight dynamic ontologies have advanced interoperability capabilities, limitations persist in achieving real-time semantic adaptability, dynamic ontology generation, and standardized cross-platform integration. Continued research is necessary to develop scalable, secure, and dynamic semantic interoperability frameworks capable of supporting the complex, data-intensive requirements of Industry 4.0 applications.

Table 1. Analysis of related work

	Related work research reference				
Attributes	[79]	[80]	[73]	[81]	[82]
Support real time	No	No	Yes	No	No
Dynamic interoperable	No	No	Yes	No	No
Suitable for small scale	Yes	Yes	No	Yes	No
Suitable for large scale	Yes	No	Yes	Yes	Yes
Latency	Medium	High	High	Medium	High
Energy consumption	Medium	Medium	High	Medium	High
Network usage	Medium	High	Medium	Medium	High
Deployment cost	High	Low	High	High	Medium
Fog based	Yes	No	No	Yes	No

3.6. Comparative analysis and discussion

Semantic interoperability within IoT ecosystems is a cornerstone for achieving seamless data exchange and integration in Industry 4.0 environments. While earlier studies have explored the impact of semantic technologies such as ontologies, middleware, and semantic web services, they have not explicitly addressed the influence of dynamic semantic alignment and cross-domain adaptability in real-time industrial contexts. This study investigated the classification and effectiveness of semantic interoperability frameworks, revealing that the lack of universally accepted semantic models and real-time adaptability remains a significant gap in existing research.

We found that semantic interoperability approaches can be broadly categorized into two types: static and dynamic. Static semantic interoperability relies on predefined, shared ontologies and standardized data formats to ensure consistency across systems. Although this approach supports semantic clarity, it limits adaptability in rapidly evolving environments. In contrast, dynamic semantic interoperability enables real-time interpretation and alignment of data without prior agreements, using middleware architectures, semantic web services, and ontology mapping APIs. Our taxonomy and literature review identified that dynamic approaches are better suited for heterogeneous and scalable Industry 4.0 applications, though they often introduce complexity and latency.

Comparative analysis of recent frameworks highlights key trade-offs. Fog-assisted semantic models [79], [81] improve latency and scalability by processing data closer to the source but typically depend on static ontologies. Rahman and Hussain [73] proposed a lightweight dynamic ontology that enhances adaptability using machine learning, though it suffers from clustering-induced delays. Unified semantic engines [82] offer scalable architecture validated in smart city deployments but lack generalizability across industrial domains. These findings suggest that higher semantic adaptability is not inherently associated with poor performance; rather, hybrid models that combine fog computing with dynamic ontology management may offer optimal balance between flexibility and efficiency.

Despite the diversity of proposed solutions, several limitations persist. Many frameworks are domain-specific and lack modularity, reducing their applicability to cross-industry scenarios. Static models fail to accommodate evolving data structures and device types, while dynamic models often require significant computational resources and introduce latency. Furthermore, the absence of standardized APIs and semantic mediation protocols hinders interoperability across platforms and vendors. These limitations impact the scalability, reliability, and economic feasibility of Industry 4.0 deployments.

Our study demonstrates that dynamic semantic frameworks are more resilient than static models in handling heterogeneous data environments. Future research should explore the integration of lightweight dynamic ontologies with edge AI and federated learning to enable real-time semantic adaptation while preserving privacy and minimizing latency. Additionally, the development of domain-agnostic semantic frameworks and standardized middleware solutions will be essential for achieving scalable and interoperable industrial ecosystems.

Recent observations suggest that semantic fragmentation, rather than device proliferation, is the primary barrier to achieving comprehensive interoperability in Industry 4.0. Our findings highlight that this phenomenon is associated with limitations in semantic adaptability and cross-platform alignment. Addressing these challenges through dynamic, scalable, and standardized semantic solutions will be critical for unlocking the full operational and economic potential of Industry 4.0 IoT systems.

4. CONCLUSION

This study has examined various research approaches proposed to address semantic interoperability challenges within the Industry 4.0 IoT ecosystem. Through the analysis of existing literature, six primary challenges associated with the absence of semantic interoperability were identified. These issues have been shown to undermine the performance, scalability, and operational efficiency of Industry 4.0 IoT applications. Without addressing these semantic gaps, Industry 4.0 systems are constrained in their ability to fully adopt emerging technological advancements such as edge AI, fog computing, and real-time distributed intelligence, ultimately hindering innovation and sustainable system development.

Among the existing approaches, the literature highlights a strong emphasis on the development of lightweight ontologies tailored for resource-constrained IoT devices such as sensors, actuators, and RFID tags. While lightweight semantic models improve computational efficiency and energy consumption, they often lack the expressive power required for full semantic interoperability in heterogeneous industrial environments. This creates a notable trade-off between semantic richness and system performance, warranting further research into adaptive ontology models capable of balancing complexity with operational constraints. Another key gap identified is the domain-specific nature of most existing semantic interoperability frameworks. Many current solutions are designed for vertical applications such as healthcare, smart cities, or precision agriculture. However, the heterogeneous, cross-domain environment of Industry 4.0 demands generalized, modular, and reusable interoperability solutions. Developing a standardized, scalable semantic model capable of supporting multiple domains within an industrial IoT context remains an open research challenge.

Additionally, the literature reveals that while static semantic interoperability has been the primary focus of most studies, dynamic semantic interoperability is critical for real-time, scalable Industry 4.0 operations and remains underexplored. Given the dynamic nature of industrial IoT systems, which continuously integrate new devices, data streams, and services, there is a pressing need for adaptive semantic models that can automatically align, update, and manage ontologies in real-time without disrupting system operations. Ongoing standardization efforts by industrial alliances and academic consortia continue to address these semantic interoperability challenges. Nevertheless, defining universally applicable, domain-independent semantic frameworks remains difficult due to the inherent diversity of industrial datasets and contextual requirements across applications.

In conclusion, the achievement of scalable, secure, and dynamic semantic interoperability is fundamental to the future success of Industry 4.0 IoT ecosystems. Future research should prioritize the development of lightweight yet expressive dynamic ontologies, domain-agnostic semantic frameworks, and real-time semantic mediation mechanisms. In particular, integrating machine learning techniques for automated ontology evolution, designing middleware that supports cross-platform semantic alignment, and validating frameworks in real-world industrial settings are essential next steps. Addressing these research gaps will be essential for advancing the practical deployment of Industry 4.0 technologies and fostering robust, scalable, and semantically integrated industrial ecosystems.

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AUTHOR CONTRIBUTIONS STATEMENT

The corresponding author responsible for all correspondence related to the paper and ensure that the other authors are included in the communication regarding submission, revision, and publication processes. Each author's contribution is as in table follows:

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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