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SEMANTIC INTEROPERABILITY IN INDUSTRY 4.0: A SYSTEMATIC MAPPING STUDY ON INTEGRATING KNOWLEDGE GRAPHS WITH AAS AND OPC UA

Industry 4.0 and the rise of collaborative value chains necessitate seamless data integration across organizational and technological boundaries. Yet the fragmented standardization environment prevents interoperability across systems and within frameworks like the Digital Twin (DT). While the Asset Administration Shell (AAS) and Open Platform Communications (OPC) Unified Architecture (UA) are established as core standards for digital asset representation and communication, their independent origins and differing metamodels create semantic gaps that hinder unified machine-level understanding. This systematic mapping study examines how Knowledge Graphs (KG) can bridge semantic gaps to create unified semantic models. Current research demonstrates progress in pairwise integrations, such as transforming OPC UA models into RDF graphs or synchronizing AAS repositories with graph databases. However, these efforts often remain isolated solutions that address specific integration challenges. Consequently, large-scale industrial deployment remains limited. This paper consolidates current knowledge on integrating AAS, OPC UA and KGs, contextualizing these efforts and highlights research gaps toward achieving interoperable manufacturing ecosystems.

1. INTRODUCTION

Industry 4.0 is an evolutionary step for the design, operation and optimization of modern industrial systems, driven by continuous connectivity and data-driven decision-making [1]. Within this paradigm, the seamless combination of physical assets and digital services represents an indispensable condition for competitiveness, especially in domains such as manufacturing [2]. As such, Digital Twins (DT) represent an important technological enabler of modern manufacturing systems, as they provide manufacturing systems with synchronized real-world information and operational performance insights [3]. During approximately the past two decades, DTs have developed from conceptual models [4] to deployed solutions

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across various industrial sectors, including discrete manufacturing, healthcare, smart cities [3] and the process industry [5]. Although there has been significant progress, large-scale DT deployments will continue to require managing complex, dynamic models, heterogeneous data formats and coordinating multiple twins spanning product, processes and infrastructures [6].

To address these limitations, the integration of semantic technologies, particularly ontologies, knowledge graphs (KG) and other semantic frameworks, are emphasized in recent studies in order to support the development of more intelligent DTs. Ontologies and KGs represent machine-readable descriptions of entities, relationships and constraints, therefore facilitating interoperability, knowledge sharing and automated reasoning within DT ecosystems [7]. However, the realization of this vision is also associated with ongoing challenges. These challenges are particularly evident in the context of manufacturing, in which multiple standards have emerged concerning data modeling, communication and digital representation of assets. These standards remain mostly unaligned and lack full interoperability, essential for building intelligent DTs [8]. Amongst the most prominent are Open Platform Communications (OPC) Unified Architecture (UA) and the Asset Administration Shell (AAS). OPC UA has its roots in the original OPC specification of the 1990s and evolved into a platform independent, service-oriented architecture that standardizes industrial communication from shop floor devices to enterprise systems. It provides a means of communication and includes an extensible information model and a number of domain-specific companion specifications that enable vendors to define rich, self-descriptive data structures for their equipment [9]. At the same time, the AAS was introduced as part of the German Industry 4.0 initiative as a standardized digital shell of an asset that provides a structured, life-cycle oriented digital representation of machines, components and products for interoperable data exchange between organizations [10]. Although both standards satisfy different but real industrial requirements, their independent origins and differing metamodels have resulted in a highly fragmented landscape characterized by inconsistent semantics and high costs associated with semantic alignment [11]. Furthermore, the emergence of Data Spaces increases the complexity and size of data sources that must be integrated to facilitate meaningful decision-making [12].

In this evolving ecosystem, KGs are becoming increasingly relevant to achieve semantic interoperability. By integrating heterogeneous data models and allowing machine reasoning across standards, KGs contribute to standardized data integration, cross-system connectivity and the development of intelligent DTs. Against this background, this paper conducts a systematic mapping study focusing on methods that bridge the semantic gap between AAS and OPC UA within DT implementations for manufacturing. Current integration efforts are consolidated and assessed within the broader ecosystem of DTs and Data Spaces. Key research gaps for large-scale industrial implementation are then identified. This paper thus aims to answer the following research questions:

- RQ1: What is the current state of research on KG-based approaches for achieving semantic interoperability between AAS and OPC UA within DT implementations for manufacturing?
- RQ2: What technical barriers and research gaps hinder achieving semantic interoperability and large-scale industrial deployment?

The remainder of this paper is structured as follows. Section 2 establishes the foundational background by introducing key principles and standards that address the semantic gap in manufacturing. The methodology is detailed in Section 3, followed by the results of the literature review in Section 4. Finally, Section 5 discusses the findings and their implications before Section 6 concludes the paper.

2. RELATED WORK

2.1. KNOWLEDGE GRAPHS

KGs can be defined as „[…] graph[s] of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent potentially different relations between these entities" [13]. This representation of knowledge allows for both humans and machines to interpret and reason over data connected to a KG. Enterprise KGs are one specific type of KGs, that include the ever-evolving shared knowledge in an organization, typically kept private for internal use [13]. On the Semantic Web, KGs are commonly represented using the Resource Description Framework (RDF), where data is encoded as subject-predicate-object triples and includes a standardized data model to allow for the publication and sharing of structural data [14]. The querying and manipulating of the data stored in KGs is possible through SPARQL, a World Wide Web Consortium (W3C) standardized query language for RDF [15]. In addition to supporting the querying of KGs, SPARQL also supports the graph pattern matching, filtering and aggregating of large RDF stores. Another essential component of the W3C semantic web technology stack is the Web Ontology Language (OWL) which extends RDF and RDF Schema (RDFS) to create a much richer and formal definition vocabulary including classes, properties, constraints and logical axioms, to enable automated reasoning and to clearly define the semantics of KGs [16].

An ontology is the conceptual foundation of this technology stack as it defines a formally specified model of a domain that is typically expressed in OWL/RDF and converts the basic data contained in a KG into a semantically meaningful, logically consistent representation of domain knowledge that can be queried and inferred from using languages such as SPARQL [17]. A single ontology can be used by multiple KGs, ensuring interoperability between the graphs. Domain ontologies define a specific field, such as materials science or manufacturing. To facilitate the alignment of ontologies across domains, top level ontologies such as the Basic Formal Ontology (BFO) are used. They usually specify very general categories like material entity, process, quality or role and are used as unifying tools in numerous semantic projects to support interoperability [18]. An example would be the Industrial Ontologies Foundry (IOF) Core Ontology, which is based on the BFO and captures manufacturing-wide concepts to provide a foundation for developing specialized ontologies in the target domain, e.g. specific engineering processes [19]. An efficient method for storing and utilizing ontologies and KGs is by using graph databases [20]. Graph databases are database systems that store information as a network of nodes (assets), edges (relationships) and allow for rich graph queries by using languages such as SPARQL. As a result, they are being increasingly used as backends for ontology management systems and for providing a means to ensure semantic interoperability.

2.2. DIGITAL TWINS

Across the literature, the definition of what constitutes a DT has remained ambiguous, as many industry-specific definitions exist and the term is often used broadly. Kritzinger et al. [21] propose general digital representation categories that distinguish based on differing degrees of integration between the physical and digital assets representation: a system qualifies as a DT only if automatic bidirectional data flow occurs. Related terms include digital shadow (automatic data flow from physical to digital only) and digital model (manual data flow only). Beyond integration levels, DTs may be categorized by their maturity. Saračević et al. [22] proposed a progression through four stages referred to as the 'Cognitive Engineering Journey', which culminates in the Cognitive Digital Twin (CDT) as illustrated in adapted form in Table 1.

Table 1. Cognitive Engineering Journey, adapted from [22]

Stage	Properties
Connect & Configure	• Connect DTs to physical assets • Integration of the data source • Support data collection, aggregation and exploration
Monitor & Visualize	• Enables real-time monitoring of data and automation based on rulesets • Visualization of data via Dashboards • Fosters Cross-site and Cross-fleet awareness
Analyze & Predict	• Enabled advanced analytics like system behavior analysis and failure prediction • Gives insights for optimization of the real-world asset based on DT simulations
Cognitive DT	• Utilizes semantic technologies • Enables processing of unstructured data, machine learning and pattern recognition • Support automated reasoning and decision systems

However, it is worth noting that alternative methods for classifying DTs have been proposed in the literature. For example, Abburu et al. [23] proposed a classification method of three categories: DTs (isolated models of physical systems), hybrid twins (interconnected models that predict unusual behaviour through integration) and CDTs (incorporating expert knowledge and problem-solving capabilities for unknown situations) [23]. Across these classification methods, the CDT concept combines DTs with semantic technologies, such as OWL and RDF, to enable autonomous understanding, decision-making and knowledge accumulation [8], thus positioning CDTs as an essential step toward creating self-adapting cyber-physical systems. In this context, data spaces serve as a vital data hubs for CDTs, allowing access to external data from various suppliers, partners and platforms [24]. They enable controlled data sharing across organizational boundaries while preserving data sovereignty through governance mechanisms and usage policies [25]. In principle, the continuous evolution and autonomy capabilities of CDTs can leverage this infrastructure to allow for the automatic integration and use of new data sources [8]. Therefore, organizations will be able to increase the amount of data available to their DTs through the inclusion of lifecycle data that would otherwise be unavailable, either due to outsourced operations or due to residing with other data space participants who maintain similar asset instances.

The AAS was first introduced alongside the Reference Architectural Model Industry 4.0 (RAMI 4.0) as the technical vehicle for DT representation. In the three-dimensional model 6 layers are defined: the Business Layer, Functional Layer, Information Layer, Communication Layer, Integration Layer and Asset Layer, separating physical equipment from its digital representation, connectivity, data, functions and business logic. These layers are then further broken down using the model axes. One axis describes the life cycle and value stream in accordance with International Electrotechnical Commission (IEC) 62890 and a second axis describes the hierarchy levels in accordance with IEC 62262 and IEC 61512 [26]. The AAS represents the cyber part of an Industry 4.0 component, which is tied to the asset layer via the information and communication layers. An AAS is instantiated at the appropriate hierarchy levels and covers the entire life cycle of the asset from type to instance [27]. The information and communication layers in an AAS can be implemented using the OPC UA information model and communication protocol, respectively, especially during the instance life cycle phase [28]. Together, AAS and OPC UA provide a robust foundation for modeling and implementing DTs.

3. METHODOLOGY

This paper employs the systematic mapping study methodology according to Petersen et al. [29]. The systematic mapping process begins with the definition of research questions, which establish the review scope by providing a high-level overview of a research area. Next, search strings were defined to identify primary studies within relevant scientific databases. An overview of the search strings and filter queries can be found in Table 2. The search results are initially screened for relevance using pre-defined inclusion and exclusion criteria to eliminate irrelevant studies, such as those that do not describe the intended scope as one of the main contributions or those included mistakenly due to ambiguous abbreviations. Duplicates, proceedings metadata and volume entries are removed during the screening process. Afterwards, a form of clustering and filtering called abstract keywording is applied. Keywords related to concepts are identified from the abstracts to develop a multi-dimensional classification framework representing the state of the art. Finally, full-text screening and full-paper analysis is performed to classify the studies in the framework while documenting a brief rationale for each classification. This phase focuses on frequency analysis across categories to identify research gaps, which are ultimately visualized through a systematic map. By adopting a systematic approach in conducting the literature review, the aim is to provide a robust foundation for deriving essential insights regarding semantic grounding for DT technologies in manufacturing.

Table 2. Used search strings and filtering queries during the systematic literature analysis

Nr	Search String / Filter Query
1	(("Asset Administration Shell") AND ("Knowledge Graph" OR "Ontolog*" OR "Semantic Interoperability" OR "RDF" OR "OWL")) OR (("OPC UA" OR "OPC Unified Architecture") AND ("Knowledge Graph" OR "Ontolog*" OR "Semantic Interoperability" OR "RDF" OR "OWL")) AND ("Digital Twin*" OR "Digital Shadow*" OR "Cognitive Twin*")
2	("Asset Administration Shell" OR "Industry 4.0" OR "Opc Ua" OR "Ontolog*" OR "Interoperability" OR "Digital Twin*" OR "Semantic Interoperability" OR "Semantics" OR "Semantic Web" OR "Internet of Things" OR "Industry 4.0" OR "Knowledge Graph*" OR "Smart Manufacturing" OR "Automation" OR "IIoT" OR "Information Model" OR "Data Integration" OR "Knowledge Representation" OR "AAS")
3	(("OPC UA" OR "OPC Unified Architecture") OR ("Industry 4.0" OR "Asset Administration Shell" OR "AAS" OR "Digital Twin")) AND ("Knowledge Graph*" OR "Ontolog*" OR "OWL" OR "RDF")
4	("Mapping" OR "Transformation" OR "Alignment") AND ("AAS" OR "Asset Administration Shell" OR "RDF" OR "OWL" OR "Ontolog*" OR "Knowledge Graph*" OR "Linked Data" OR "Semantic Web" OR "OPC UA" OR "OPC Unified Architecture")

4. QUANTITATIVE REVIEW

In this section, an overview of the literature review findings is provided. The study used three databases, namely Scopus, Web of Science and Association for Computing Machinery Digital Library (ACM DL), which were selected for their extensive coverage of articles, conference proceedings and journals in computer science, engineering and industrial technology. During initial database screening, it became apparent that only a limited number of publications address OPC UA, AAS and KGs collectively. Consequently, a broader scope was adopted to capture the intended research landscape. Search String 1 was applied via the advanced search functionality on all three databases, resulting in a combined total of 607 publications. Following removal of duplicate records, conference proceedings and volumes, 378 publications were available for further consideration. As shown in Fig. 1, the publication data shows minimal research activity prior to 2015, with only four publications across all databases before 2000. Following this period, exponential growth is observed across all three databases, with peak output in 2025 (51 articles in both ACM DL and Scopus, 19 in Web of Science). This sharp increase in recent years suggests rapidly growing academic interest in the research topic.

Due to the large number of articles published after 2015, the literature was filtered to include articles published from 2015 onward only, reducing the dataset to 344 entries. Bibliometric analysis using Bibliometrics revealed two keyword clusters: one related to biomedicine and one related to the review scope (engineering, computer science and industrial technology). The second keyword cluster was selected and retained through application of filter query 2. To ensure comprehensive capture of all remaining relevant literature, filter queries 3 and 4 were applied to further refine the corpus. Filter query 3 targeted publications that explicitly combined industrial standards (e.g. OPC UA, AAS, Industry 4.0) with semantic technologies, whereas filter query 4 targeted methodological literature focused on mapping, transformation or alignment between these areas. As such, their results were merged to create a corpus of 49 publications. Seven publications were inaccessible and therefore removed from the corpus. The screening criteria required that publications explicitly address the integration of KGs with DTs, AAS or OPC UA in a manufacturing context. Publications that only referenced these concepts in the abstract and did not provide any substantive conceptual treatment regarding their research contribution were not included in the screening. Through citation analysis, four additional relevant references were added to the corpus, resulting in a final literature corpus of 32 publications.

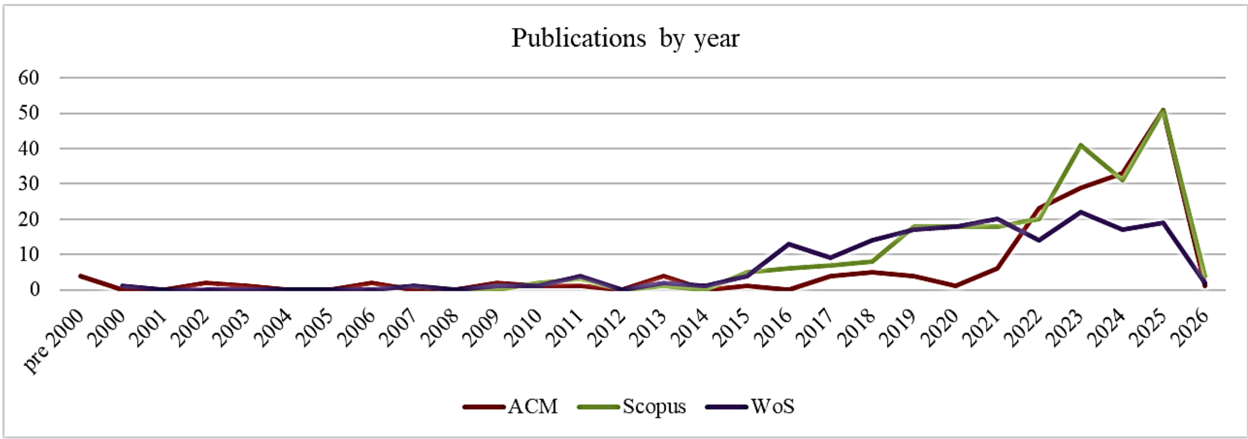

Fig. 1. Publications by year, categorized by respective database

5. SYSTEMATIC MAPPING STUDY DISCUSSION

This systematic mapping study provides an overview of the research landscape which is characterized by substantial technical development yet still lacks industry-related maturity with regards to thorough semantic interoperability between KGs, OPC UA and the AAS. This chapter classifies the literature corpus and identifies clusters regarding the contribution topic, contribution type and research type. In addition, a technology pairing analysis is performed.

5.1. RESEARCH TYPE DISTRIBUTION

The systematic map, classification of publication by the research type and classification of publication by the technology combination are illustrated in Figure 2. Publications were classified by a single research type but could span multiple contribution topics and types. The bubble size indicates the number of publications in each category.

The research type distribution reveals a pronounced over-representation of validation research, which accounts for 23 of the 32 analysed publications. Most of the publications investigating combinations of KGs with OPC UA or AAS have been developed either in a laboratory setting or as proofs-of-concept rather than deployment in real-world industrial settings. Studies documenting technical feasibility through controlled experiments include: foundational mappings from OPC UA to OWL and early AAS semantic representations [28, 30, 40, 53], event-driven AAS synchronization and self-configuring agent architectures [36, 37, 56, 58], semantic validation frameworks for industrial standards [38, 39, 44], AI-based inference systems using reinforcement learning and LLMs [31, 41, 57, 60], KG-based production planning prototypes [42, 43, 59] and vertical integration architectures for federated data exchange [33–35, 37, 51, 55]. Although these contributions demonstrate the technical feasibility, their findings have limited applicability in production environments.

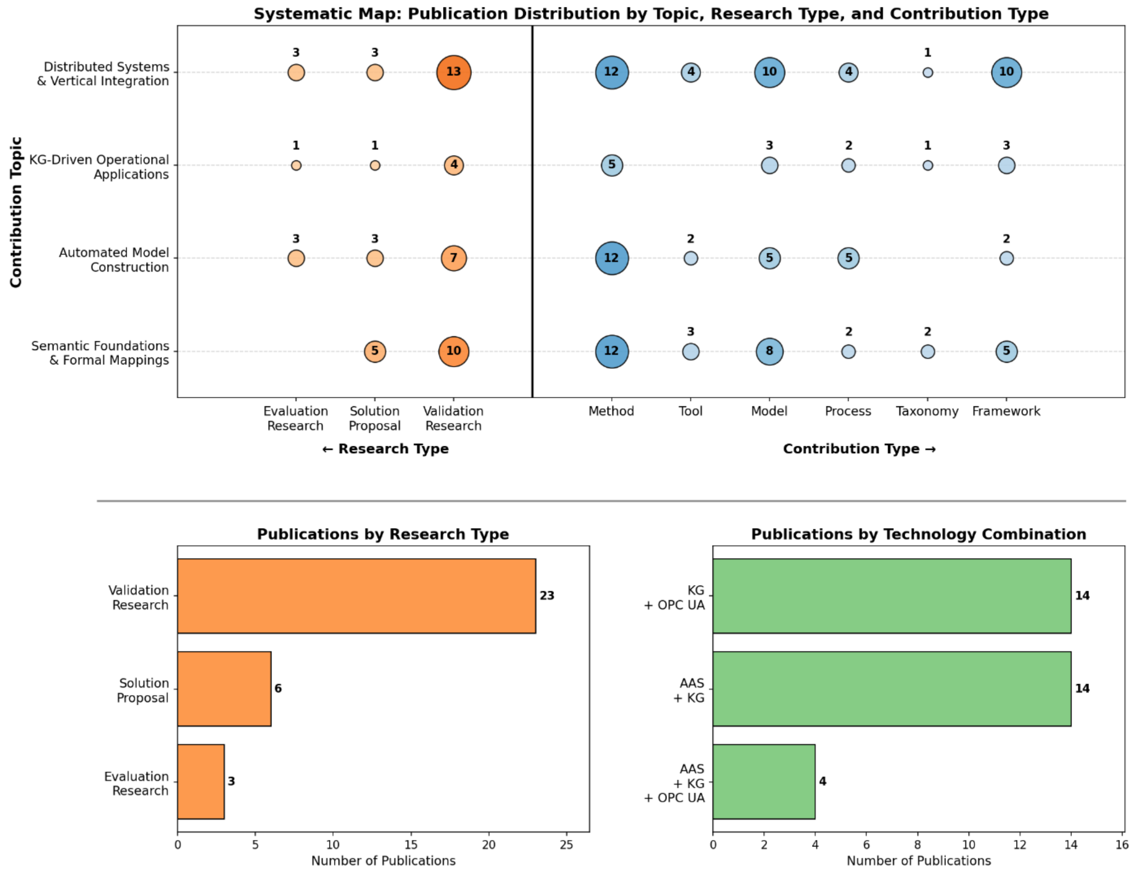

Fig. 2. Visualization of the systematic map as well as publications by their research type and technology combination, created using matplotlib

Six publications comprise the second category of solution proposals. These include ontological frameworks for the AAS [45, 46] and the Digital Product Passport [47], bidirectional mapping approaches for capability models [48] and automated OPC UA information model construction methods [49, 50]. The contributions of this category form an important foundation for the development of conceptual work but require further validation to determine the practical viability.

Evaluation research remains notably scarce, as only three studies report on implementation in actual production environments. Wang et al. [51] utilized a KG constructed from OPC UA process data to validate their anomaly detection model in an aerospace machining workshop. Schaper et al. [52] used the RDF serialization of the AAS and engineering data from a laser cutting machine manufacturer to generate simulation models automatically, thus creating behavioral models with minimal input. Jirkovský et al. [54] deployed a semantic big data historian at a hydroelectric power plant, transforming high-frequency data from 38 sensors into over 5 million daily RDF triples to optimize turbine restart timing. The scarcity of real-world implementation indicates that quantifiable metrics of successful deployment in the industry and documented evidence regarding operational implications remain largely absent.

5.2. CONTRIBUTION TOPICS AND SOLUTION APPROACHES

The integration of KGs into Industry 4.0 environments is motivated by the technical and operational gaps that existing standards, such as OPC UA and the AAS, cannot resolve in isolation. While these standards provide the foundation for syntactic interoperability, they lack the formal logic, lifecycle-spanning integration, and automated reasoning required for CDTs. This section categorizes the fundamental research problems identified across the 32 analysed sources and details the KG-based solution approaches implemented to bridge these gaps. Based on thematic analysis, four contribution topics emerged (Fig. 2):

- C1: Semantic Foundations and Formal Mapping,
- C2: Automated Model Construction,
- C3: KG-driven Operational Applications,
- C4: Distributed Systems and Vertical Integration.

Table 3 presents the literature mapping matrix, indicating each publication's contribution to these topics.

The contribution topic 'Semantic Foundations and Formal Mappings' (C1) addresses a primary challenge: OPC UA information models and AAS metamodels contain implicit semantics inaccessible to machine logic. OPC UA is less expressive than OWL, as it cannot natively define complex axioms [30]. This prevents production machines from autonomously acting on contextual information during system reconfiguration or runtime [31]. Similarly, standard AAS serializations specify only syntactic structure, offering no formal basis for logical inference [40, 46]. Semantic lifting approaches address this gap by transforming OPC UA address spaces or AAS models into ontologies via formal mapping rules. Grangel-González et al. [53] proposed an RDF-based vocabulary for the AAS, providing unified identification across organizational boundaries. Subsequent work demonstrated that mapping OPC UA namespaces to OWL enabled production machines to autonomously interpret contextual requirements, such as sensor presence or tool reconfiguration [31], while reducing implementation complexity by utilizing W3C technologies [30]. Further contributions formalized the RAMI 4.0 AAS structure ontologically and linked field-level OPC UA data to AAS shells via domain ontology bridges [28, 35]. Bidirectional mapping approaches extend semantic lifting to enable round-trip transformation between AAS and ontology representations. Vieira de Silva et al. [48] established bidirectional mapping rules between the AAS JSON serializations and a domain specific ontology, bridging incompatible technical formats for capability and skill modeling. Validation-oriented approaches tackle a second problem: industrial modeling guidelines are frequently provided as unstructured PDF documents, making manual validation error-prone and non-scalable [38, 39]. KG-based solutions employ the Shapes Constraint Language (SHACL) and SPARQL rules to implement semantic validation layers that enforce compliance in respect to domain-specific standards. Bader et al. [40] demonstrated that SHACL shapes provide feasible data quality assurance, while Wagner [39] extended this to validate distributed KGs and complex type hierarchies. Bareedu et al. [38] advanced automation further by leveraging large language models (LLMs) to semi-automatically extract modeling constraints from 28 companion specifications.

Table 3. Literature mapping matrix according to contribution topics

Author(s) sorted by Year	C1	C2	C3	C4
Grangel-González et al. (2016) [53]	●			
Jirkovský et al. (2018) [54]		●		●
Bader et al. (2019) [40]	●			
Bakakeu et al. (2019) [31]	●	●		
Gil et al. (2019) [33]				●
Schiekofer et al. (2019) [30]	●			
Bakakeu et al. (2020) [41]		●		
Katti et al. (2020) [55]		●		●
Müller et al. (2020) [45]	●			●
Mehling et al. (2021) [35]	●			●
Huang et al. (2022) [46]	●	●		
Weiss et al. (2022) [28]	●			●
Bozkurt et al. (2023) [42]			●	
Huang et al. (2023) [44]		●		●
Pereira et al. (2023) [56]				●
Wang et al. (2023) [32]		●		●
Vieira da Silva et al. (2023) [48]	●	●		
Wang et al. (2023) [50]				●
Yu et al. (2023) [49]	●	●		
Bareedu et al. (2024) [38]	●			
Friedrich et al. (2024) [37]				●
Kalach et al. (2024) [34]				●
Li et al. (2024) [57]		●		
Hurtado et al. (2025) [58]			●	
Kosse et al. (2025) [59]	●		●	●
Pourjafarian et al. (2025) [47]			●	●
Sapel et al. (2025) [43]			●	●
Schaper et al. (2025) [52]		●	●	●
Shi et al. (2025) [60]		●		●
Sonnenberg et al. (2025) [36]	●			●
Wagner (2025) [39]	●			
Wang et al. (2025) [51]		●		●

Recent work applies these validation principles to synchronize AAS repositories into KGs for structural validation [36] and to harmonize Industry 4.0 standards with domain-specific data management in construction [59]. Collectively, these approaches position the KG as a logical processing layer above the communication (OPC UA) and structural (AAS) layers, transforming passive node networks into systems capable of autonomous interpretation and standards-compliant operation [39, 46].

Building on these semantic foundations, the contribution topic ‘Automated Model Construction’ (C2) addresses the scalability demands of modular production and ‘lot size one’ manufacturing, which require rapid reconfiguration and integration of new assets [55]. However, manually constructing OPC UA information models or AAS submodels is a labor-intensive bottleneck [49, 57]. Additionally, manually created models are frequently incomplete or inconsistent, failing to capture the complex relationships needed for comprehensive data integration [32, 41]. Automated model generation approaches leverage formal mappings of C1 to enable automated matchmaking. Huang et al. [46] tagged AAS models with manufacturing ontology concepts, allowing automatic transformation to OWL instances for capability reasoning. Building on this, another paper demonstrated that assembly tasks could be automatically matched to specific robotic resources by querying the resulting KG with SPARQL [44]. Schaper et al. [52] applied similar transformations to virtual commissioning, combining the AAS RDF serialization with domain ontologies to automatically generate executable simulation models. However, automated model construction must also address the diversity and dynamic nature of manufacturing data sources. For high-velocity sensor data, Jirkovský et al. [54] developed a semantic big data historian that parses self-describing metadata to automatically extend the ontology for unknown devices. For existing databases, Yu et al. [49] demonstrated using a graph-based KG as an intermediate bridge to generate compliant OPC UA NodeSets. For unstructured documentation, Shi et al. [60] fine-tuned LLMs to convert proprietary PDF datasheets into standardized AAS instances linked to ECLASS dictionaries. Complementing these source-oriented approaches, Wang et al. [32, 51] addressed the temporal dimension by combining time-series learning with KG embeddings to discover hidden manufacturing relationships and predict anomaly propagation routes, enabling proactive maintenance through learned temporal features that static models cannot capture.

While C1 and C2 provide semantic infrastructure and automated modeling pipelines, the contribution topic ‘KG-driven Operational Applications’ (C3) extends generic Industry 4.0 standards with specialized ontologies to address domain-specific requirements that AAS submodel templates or OPC UA companion specifications do not cover. Kosse et al. [59] harmonized AAS with construction-specific data management standards, creating a KG that serves as the single source of truth across building lifecycle phases. This was demonstrated by dynamically adjusting a curing oven’s heat output based on comparing static thresholds against live sensor values. Pourjafarian et al. [47] integrated AAS submodels into a digital product passport ontology. The ontology was built utilizing reusable design patterns, enabling SPARQL-based retrieval of material composition and damage types to support end-of-life repair or recycling decisions. Intelligent resource management leverages KG reasoning capabilities for automated planning in dynamic production environments. Bozkurt and Schulz [42] used a specialized ontology to model product-process-resource hierarchies, with the AAS providing semantic self-descriptions and the KG enabling multi-criteria resource selection. This approach was validated at a research campus with a pool of resources and two distinct products. Sapel et al. [43] extended this pattern across company boundaries, automatically matching customer inquiries against technical properties of injection molding equipment by querying an ontology-based graph database populated with AAS data. Agent-based self-configuration builds on the capability matching described in C2 to enable fully autonomous operation. Hurtado et al. [58] enriched AAS descriptions with an OWL-based capability-skills-services ontology, allowing industrial agents to identify their functional roles and autonomously perform distributed negotiation.

While the preceding contribution topics establish semantic foundations, automate model construction and demonstrate domain-specific applications, these capabilities remain isolated without mechanisms to integrate data across organizational boundaries and automation levels. Contribution Topic 4, 'Distributed Systems and Vertical Integration', addresses this integration challenge. The DT ecosystem is fragmented: data silos span the product lifecycle and value chain, from field-level sensors to enterprise software [28, 34, 59]. Proprietary naming conventions and formats further prevent unified machine-level understanding [43, 60]. Federated architectures preserve local data ownership while enabling global queryability. Kalach et al. [34] developed a system in which autonomous nodes store OPC UA sensor data as local KGs, while parent nodes merge child-metadata when queried. This enables queries across the entire system as a single network. Sonnenberg et al. [36] applied event-driven synchronization via Apache Kafka to maintain consistency between AAS repositories and a central KG, validated by identifying specific software versions across 1000 robots to trigger targeted updates. Protocol mediation enables interoperability across heterogeneous Internet of Things (IoT) platforms. Gil and Zapata-Madrigal [33] demonstrated that an ontology can provide a shared semantic language for distributed actors. Pereira et al. [56] extended this to coordinate 10 sensors and 7 actuators using heterogeneous protocols, translating disparate data into a homogeneous KG with each physical asset assigned an AAS-based DT. Sovereign data exchange addresses intellectual property concerns in cross-company scenarios. Friedrich et al. [37] structured operational and engineering data using AAS and OPC UA as RDF, enabling metadata enrichment and sovereign exchange. Vertical integration approaches complement this by bridging field-level and enterprise systems. The proposed concept by Weiss and Ihlenfeldt [28] linked OPC UA field data to AAS shells via a domain ontology bridge, avoiding commitment to a single meta-model. Several papers contribute to C4 through aspects already detailed in C3: Kosse et al. [59] and Pourjafarian et al. [47] achieve vertical integration through their domain-specific ontology alignments, while Schaper et al. [52] integrates data both vertically within toolchains and horizontally across company borders.

5.3. TECHNOLOGY COMBINATION ANALYSIS

Examination of technology coverage across the corpus reveals distinct integration patterns reflecting both the maturity of underlying standards and recognized challenges in semantic interoperability. OPC UA and KG as well as AAS and KG integration have been equally prominent with respectively 14 publications each, reflecting the maturity of both standards within Industry 4.0 and the recognized need to overcome their respective semantic limitations. OPC UA has established itself as a robust industrial communication standard facilitating syntactic interoperability, while the AAS provides a standardized structural framework for digital asset representation.

OPC UA and KG research has transitioned from foundational formal mappings establishing transformation rules between OPC UA information models and OWL/RDF [28, 30–35] to increasingly complex applications: automatic model generation [49, 50], validation through formal constraints [38, 39, 41], temporal analytics supporting anomaly detection and propagation analysis [32, 51] as well as open-world knowledge completion [57]. The primary contribution types are methods (transformation rules and mapping frameworks) and models (ontological representations of OPC UA concepts).

AAS and KG mappings have progressed from early ontological formalizations of RAMI 4.0 to operational frameworks, addressing cross-company interoperability. Building on early AAS ontologization efforts [53], Bader and Maleshkova [40] formalized the Semantic AAS with RDF serialization and SHACL shapes for schema validation. Recent contributions advance along multiple trajectories: event-driven synchronization for distributed AAS repositories [36], LLM-assisted semantic matching between proprietary data and standardized dictionaries [60] and ontology-based capability checking for automated production planning [43, 44]. Contribution types in this cluster range from methodologies (bidirectional mapping rules) and models (domain ontologies aligned with AAS) to emerging architectural frameworks for system-level integration.

Integrated approaches combining all three core technologies remain notably scarce. Only four studies address this full stack. Friedrich et al. [37] connect AAS, OPC UA endpoints and external services within a GAIA-X federated learning architecture. Weiss and Ihlenfeldt [28] as well as Mehling et al. [35] present a similar approach to link OPC UA field data to AAS shells, avoiding commitment to a single meta-model. Pereira et al. [56] implemented an IoT gateway middleware, utilizing ontologies for device identification, the AAS for asset representation and OPC UA as the communication protocol. This scarcity indicates a significant research gap in semantic interoperability pipelines which simultaneously address machine-level communication, standardized asset representation, semantic reasoning capabilities and vertical integration.

6. CONCLUSION

This systematic mapping study analysed 32 publications investigating KG-based approaches for semantic interoperability within DT implementations for manufacturing, with particular focus on AAS and OPC UA integration.

Regarding the current state of research (RQ1), four contribution topics emerged from thematic analysis: semantic foundations and formal mappings (C1), automated model construction (C2), KG-driven operational applications (C3), and distributed systems with vertical integration (C4). Technology combination analysis revealed equally mature research streams for OPC UA–KG and AAS–KG integration (14 publications each), yet architectures combining all three technologies remain scarce (4 publications). Research has progressed from foundational OWL/RDF mappings toward operational frameworks addressing capability matching, production planning, and cross-company interoperability. However, the dominance of validation research (23 publications) over evaluation research (3 publications) indicates that while technical feasibility has been established, industrial deployment and best practices have not yet matured.

Regarding technical barriers and research gaps (RQ2), four persistent challenges were identified across the contribution topics: (1) the absence of empirical evidence from production deployments and quantifiable operational metrics [30, 56]; (2) the reliance on necessary expert intervention for semantic annotation, ontology alignment, and model maintenance despite existing solution approaches [38, 46, 55]; (3) computational limitations causing synchronization delays and reasoning complexity in distributed architectures [36, 39]; and (4) information loss during model transformations due to differing expressivity between OPC UA, AAS and OWL [31, 44, 48, 49]. Additionally, the scarcity of full-stack architectures addressing machine-level communication, asset representation, and semantic reasoning within unified pipelines represents a significant integration gap.

This study is limited to research explicitly addressing AAS or OPC UA in conjunction with KGs. Adjacent work on technology-agnostic ontology alignment and domain-specific vocabularies, while relevant, was excluded. The findings confirm that KG-based approaches can technically bridge semantic gaps across manufacturing resources, processes and products. However, the transition from laboratory demonstrations to scalable industrial deployment remains incomplete. To achieve industrial maturity, research must transition from laboratory validations to production evaluations, and automated tooling must reduce expert reliance. Notably, toolsets utilizing DTs and KGs are actively emerging [35, 37, 44] and LLM-based approaches for automated semantic annotation show considerable promise [38, 60]. As manufacturing ecosystems increasingly demand cross-organizational interoperability, the integration of KGs with established standards such as AAS and OPC UA represents a critical enabler for realizing the vision of CDTs.

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REFERENCES

[1] JAZDI N., 2014, *Cyber Physical Systems in the Context of Industry 4.0*, IEEE International Conference on Automation, Quality and Testing, Robotics, Cluj-Napoca, Romania, IEEE, Cluj-Napoca, Romania, 1–4, http://ieeexplore.ieee.org/document/6857843/.

[2] FULLER A., FAN Z., et al., 2020, *Digital Twin: Enabling Technologies, Challenges and Open Research*, IEEE Access, 8, 108952–108971.

[3] TAO F., ZHANG H., et al., 2019, *Digital Twin in Industry: State-of-the-Art*, IEEE Transactions on Industrial Informatics, 15/4, 2405–2415.

[4] GRIEVES M., 2014, *Digital Twin: Manufacturing Excellence Through Virtual Factory Replication*. LLC, White Paper, 1–7.

[5] PERNO M., HVAM L., et al., 2022, *Implementation of Digital Twins in the Process Industry: a Systematic Literature Review of Enablers and Barriers*, Computers in Industry, 134, 103558.

[6] SAHLAB N., KAMM S., et al., 2021, *Knowledge Graphs as Enhancers of Intelligent Digital Twins*, 2021 4th IEEE International Conference on Industrial Cyber-Physical Systems (ICPS), Victoria, BC, Canada, IEEE, Victoria, BC, Canada, 19–24, https://ieeexplore.ieee.org/document/9468219/.

[7] KARABULUT E., PILEGGI S.F., et al., 2024, *Ontologies in Digital Twins: A Systematic Literature Review*, Future Generation Computer Systems, 153, 442–456.

[8] ZHENG X., LU J., et al., 2022, *The Emergence of Cognitive Digital Twin: Vision, Challenges and Opportunities*, International Journal of Production Research, 60/24, 7610–7632.

[9] LADEGOURDIE M., KUA J., 2022, *Performance Analysis of OPC UA for Industrial Interoperability Towards Industry 4.0*, IoT, 3/4, 507–525.

[10] PLATTFORM INDUSTRIE 4.0, 2022, *Details of the Asset Administration Shell – Part1: The Exchange of Information Between Partners in the Value Chain of Industry 4.0* (Version 3.0RC02), Berlin, https://www.plattformi40.de/IP/Redaktion/EN/Downloads/Publikation/Details_of_the_Asset_Administration_Shell_Part1_V3.html.

[11] MELLUSO N., GRANGEL-GONZALEZ I., et al., 2022, *Enhancing Industry 4.0 Standards Interoperability Via Knowledge Graphs with Natural Language Processing*, Computers in Industry, 140, 103676.

[12] CZVETKO T., ABONYI J., 2023, *Data Sharing in Industry 4.0 – Automation ML*, B2MML and International Data Spaces-based solutions, Journal of Industrial Information Integration, 33, 100438.

[13] HOGAN A., BLOMQVIST E., et al., 2022, *Knowledge Graphs*, ACM Computing Surveys, 54/4, 1–37.

[14] GIBBINS N., SHADBOLT N., 2011, *Resource Description Framework (RDF)*, BATES M.J. (ed.), Understanding Information Retrieval Systems, Auerbach Publications, 635–648, https://www.taylorfrancis.com/books/9781439891995/chapters/10.1201/b11499-53.

[15] HARRIS S., SEABORNE A., 2013, *Sparql 1.1 Query Language*, W3C, https://www.w3.org/TR/sparql11-query/.

[16] BOCK C., FOKOUE A., et al., 2012, *OWL 2 Web Ontology Language*, W3C, https://www.w3.org/TR/owl2-overview/.

[17] GUARINO N., OBERLE D., et al., 2009, *What is an Ontology?*, STAAB S., STUDER R. (eds.), Handbook on Ontologies, Springer Berlin Heidelberg, Berlin, Heidelberg, 1–17, http://link.springer.com/10.1007/978-3-540-92673-3_0.

[18] ARP R., SMITH B., et al., 2015, *Building Ontologies with Basic Formal Ontology*, The MIT Press, https://direct.mit.edu/books/book/4044/Building-Ontologies-with-Basic-Formal-Ontology.

[19] KULVATUNYOU B., DROBNJAKOVIC M., et al., 2022, *The Industrial Ontologies Foundry (IOF) Core Ontology*, Formal Ontologies Meet Industry (FOMI) 2022, Tarbes, FR, https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=935068.

[20] BESTA M., GERSTENBERGER R., et al., 2024, *Demystifying Graph Databases: Analysis and Taxonomy of Data Organization*, System Designs, and Graph Queries, ACM Computing Surveys, 56/2, 1–40.

[21] KRITZINGER W., KARNER M., et al., 2018, *Digital Twin in Manufacturing: A Categorical Literature Review and Classification*, IFAC-PapersOnLine, 51/11, 1016–1022.

[22] SARACEVIC F., 2017, *Cognitive Digital Twin*, Bosnia.

[23] ABBURU S., BERRE A.J., et al., 2020, *COGNITWIN – Hybrid and Cognitive Digital Twins for the Process Industry*, 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Cardiff, UK, IEEE, Cardiff, UK, 1–8, https://ieeexplore.ieee.org/document/9198403/.

[24] JARKE M., OTTO B., et al., 2019, *Data Sovereignty and Data Space Ecosystems*, Business & Information Systems Engineering, 61/5, 549–550.

[25] MÖLLER F., JUSSEN I., et al., 2024, *Industrial Data Ecosystems and Data Spaces*, Electronic Markets, 34/1, 41.

[26] DIN, 2016, DIN SPEC 91345:2016-04 – *Reference Architecture Model Industrie 4.0* (RAMI4.0), https://www.dinmedia.de/de/technische-regel/din-spec-91345/250940128.

[27] BEDEN S., CAO Q., et al., 2021, *Semantic Asset Administration Shells in Industry 4.0: A Survey*, 4th IEEE International Conference on Industrial Cyber-Physical Systems (ICPS), Victoria, BC, Canada, IEEE, Victoria, BC, Canada, 31–38, https://ieeexplore.ieee.org/document/9468266/.

[28] WEISS A., IHLENFELDT S., 2022, *Integration of OPC UA Information Models into Enterprise Knowledge Graphs*, Journal of Machine Engineering, 22/2, 138–147.

[29] PETERSEN K., FELDT R., et al., 2008, *Systematic Mapping Studies in Software Engineering*, Proceedings of the 12th International Conference on Evaluation and Assessment in Software Engineering, Swindon, GBR, BCS Learning & Development Ltd., Swindon, GBR, 68–77.

[30] SCHIEKOFER R., GRIMM S., et al., 2019, *A Formal Mapping Between OPC UA and the Semantic Web*, 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), Helsinki, Finland, IEEE, Helsinki, Finland, 33–40, https://ieeexplore.ieee.org/document/8972102/.

[31] BAKAKEU J., BROSSOG M., et al., 2019, *Automated Reasoning and Knowledge Inference on OPC UA Information Models*, 2019 Ieee International Conference On Industrial Cyber Physical Systems (ICPS 2019), 345 E 47TH ST, NEW YORK, NY 10017 USA, IEEE, 345 E 47TH ST, NEW YORK, NY 10017 USA, 53–60.

[32] SHENGBO W., GUO Y., 2023, *Knowledge-Driven Analysis Framework of Anomaly Propagation in Manufacturing Workshop*, Institute of Electrical and Electronics Engineers Inc., 58–62, https://www.scopus.com/inward/record.uri?eid=2-s2.0. 85190674088&doi=10.1109%2FAEIS61544.2023.00017&partnerID=40&md5=4feab6bb278b7b282bda5be2698e 84c8.

[33] GIL S., ZAPATA-MADRIGAL G.D., 2019, *Semantic Automation Systems, a Suitable Approach for Automation Networks in The Industry 4.0*, 2019 IEEE 4th Colombian Conference on Automatic Control (Ccac): Automatic Control As Key Support of Industrial Productivity, 345 E 47th St, New York, Ny 10017 Usa, Ieee, 345 E 47th St, New York, Ny 10017 USA.

[34] EL KALACH F., SOLANKI J., et al., 2024, *A Federated Information System Framework for Vertical Integration*, Manufacturing Letters, 41, 1192–1199.

[35] MEHLING C.W., WENZEL K., et al., 2021, *Intelligent Production Systems Through Semantic Interoperability of All Assets – Linked Data for Selfoptimizing Manufacturing*; Intelligente produktionssysteme durch semantische interoperabilität aller komponenten- linked data für die selbst -optimierende produktion, WT Werkstattstechnik, VDI Fachmedien GmBbH & Co., 111/4, 251–255.

[36] SONNENBERG G., STEIN P., et al., 2025, *Queryable AAS Graphs for AI Agents: An Event-Driven Knowledge Graph Integration for AAS Environments*, IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, https://www.scopus.com/inward/record.uri?eid=2-s2.0-105021809897&doi=10.1109%2FETF A65518.2025. 11205691&partnerID=40&md5=ff87a1fe2481c511e57225c31d5d7f15.

[37] FRIEDRICH C., VOGT S., et al., 2024, *Enabling Federated Learning Services Using OPC UA, Linked Data and GAIA-X in Cognitive Production*, Journal of Machine Engineering, 24/2, 18–33.

[38] BAREEDU Y.S., FRUEHWIRTH T., et al., 2024, *Deriving Semantic Validation Rules from Industrial Standards: an OPC UA Study*, SEMANTIC WEB, 15/2, 517–554.

[39] WAGNER M., 2025, *Validating System Behavior in OPC UA Using Semantic Web Technologies*, IFAC-PapersOnLine, Elsevier B.V., 59, 155–160, https://www.scopus.com/inward/record.uri?eid=2-s2.0-1050269 30456&doi=10.1016%2Fj.ifacol.2025.11.941&partnerID=40&md5=c869e7318bb412e1d74467bcd245bfbf.

[40] BADER S.R., MALESHKOVA M., 2019, *The Semantic Asset Administration Shell*, ACOSTA M., CUDRE-MAUROUX P., MALESHKOVA M., PELLEGRINI T., SACK H., SURE-VETTER Y. (eds.), Semantic Systems. The Power of AI and Knowledge Graphs, Springer International Publishing, Cham, 159–174, http://link.springer.com/10.1007/978-3-030-33220-4_12.

[41] BAKAKEU J., SCHAEFER F., et al., 2020, *Reasoning Over OPC UA Information Models Using Graph Embedding and Reinforcement Learning*, 2020 Third International Conference On Artificial In^{TEL} Ligence For Industries (Ai4i 2020), 10662 Los Vaqueros Circle, Po Box 3014, Los Alamitos, Ca 90720-1264 Usa, Ieee Computer Soc, 10662 Los Vaqueros Circle, Po Box 3014, Los Alamitos, Ca 90720-1264 Usa, 40–47.

[42] BOZKURT A., SCHULZ R., 2023, *Verwaltungsschale und Wissensgraphen-Basierte Planung der Produktionslogistik in Einem Fluiden Produktionssystem*, Logistics Journal: Proceedings, /19, https://proc.logistics-journal.de/article/view/1086.

[43] SAPEL P., GAROUFALI A., et al., 2025, *Leveraging Ontologies and Asset Administration Shells for Decision-Support: a Case Study on Production Planning within the Injection Molding Domain*, Internet of Things, 34, 101739.

[44] HUANG Y., DHOUIB S., et al., 2023, *Semantic Interoperability of Digital Twins: Ontology-Based Capability Checking in AAS Modeling Framework*, Ieee 6th International Conference on Industrial Cyber-Physical Systems, Icps, 345 E 47th St, New York, Ny 10017 Usa, Ieee, 345 E 47th St, New York, Ny 10017 Usa.

[45] MUELLER A.W., GRANGEL-GONZALEZ I., et al., 2020, *An Ontological View of the RAMI4.0 Asset Administration Shell*, Proceedings of The 12th International Joint Conference on Knowledge Discovery, Knowledge Engineering And Knowledge Management (Keod), Vol 2, Av D Manuell, 27a 2 Esq, Setubal, 2910-595, Portugal, Scitepress, Av D Manuell, 27a 2 Esq, Setubal, 2910-595, Portugal, 165–172.

[46] HUANG Y., DHOUIB S., et al., 2022, *Enabling Semantic Interoperability of Asset Administration Shells Through an Ontology-Based Modeling Method*, Proceedings of the 25th International Conference on Model Driven

Engineering Languages and Systems: Companion Proceedings, New York, NY, USA, Association for Computing Machinery, New York, NY, USA, 497–502, https://doi.org/10.1145/3550356.3561606.

[47] POURJAFARIAN M., PLOCIENNIK C., et al., 2025, *An ODP-Based Ontology for the Digital Product Passport*, Procedia CIRP, Elsevier B.V., 135, 930–935, https://www.scopus.com/inward/record.uri?eid=2-s2.0-105011590103&doi=10.1016%2Fj.procir.2024.12.125&partnerID=40&md5=0472abd4148f6a6d6b17a7ce76fb1cc6.

[48] VIEIRA DA SILVA L.M., KÖCHER A., et al., 2023, *Toward A Mapping of Capability and Skill Models Using Asset Administration Shells and Ontologies*, IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, Institute of Electrical and Electronics Engineers Inc., 2023-September, https://www.scopus.com/inward/record.uri?eid=2-s2.085175454408&doi=10.1109%2FETFA54631. 2023.10275459&partnerID=40&md5 =4bb2850adf1b64ef44f5a04c28610831.

[49] YU R., ZHONG Y., et al., 2023, *Leveraging Graph Databases for Automated OPC UA Information Model Construction*, Proceedings of 2023 The 12th International Conference on Networks, Communication And Computing, Icncc 2023, 1601 Broadway, 10th Floor, New York, Ny, United States, Assoc Computing Machinery, 1601 Broadway, 10th Floor, New York, Ny, United States, 294–299.

[50] WANG S., XU O., 2023, *Semantic Information Modeling and Implementation Method for Water Conservancy Equipment*, IEEE Access, Institute of Electrical and Electronics Engineers Inc., 11, 133879–133890.

[51] WANG S., GUO Y., et al., 2025, *A Deep Graph Neural Network-Based Link Prediction Model for Proactive Anomaly Detection in Discrete Manufacturing Workshop*, Journal of Manufacturing Systems, Elsevier B.V., 79, 301–317.

[52] SCHAPER S., LISTL F.G., et al., 2025, *Automatic Behavior Simulation Model Generation for Virtual Commissioning of Machine Tools Through Engineering Data Integration*, IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, Institute of Electrical and Electronics Engineers Inc., https://www.scopus.com/inward/record.uri?eid=2-s2.0-105021806453&doi=10.1109%2FETFA65518.2025.11205741&partnerID= 40&md5=2960071dd0ad4d8efdc5a95969fc9987.

[53] GRANGEL-GONZALEZ I., HALILAJ L., et al., 2016, *Towards a Semantic Administrative Shell for Industry 4.0 Components*, 2016 IEEE Tenth International Conference on Semantic Computing (ICSC), Laguna Hills, CA, IEEE, Laguna Hills, CA, 230–237, http://ieeexplore.ieee.org/document/7439338/.

[54] JIRKOVSKY V., OBITKO M., et al., 2018, *Toward Plug&Play Cyber-Physical System Components*, IEEE Transactions on Industrial Informatics, 14/6, 2803–2811.

[55] KATTI B., PLOCIENNIK C., et al., 2020, *Bidirectional Transformation of MES Source Code and Ontologies*, International Conference on Industry 4.0 And Smart Manufacturing (Ism 2019), Sara Burgerhartstraat 25, Po Box 211, 1000 Ae Amsterdam, Netherlands, Elsevier Science Bv, Sara Burgerhartstraat 25, Po Box 211, 1000 Ae Amsterdam, Netherlands, 197–204.

[56] PEREIRA P.H.M., CAINELLI G.P., et al., 2023, *Interoperability Middleware for IIOT Gateways Based on Standard Ontologies and AAS*, IFAC-PapersOnLine, Elsevier B.V., 56, 9831–9836, https://www.scopus.com/inward/record.uri?eid=2-s2.0-85184960992&doi=10.1016%2Fj.ifacol.2023.10.403& par tnerID=40&md5=9871038c092b4230b1fec96e6018a058.

[57] LI X., ZHANG S., et al., 2024, *Knowledge Graph Based OPC UA Information Model Automatic Construction Method for Heterogeneous Devices Integration*, Robotics and Computer-Integrated Manufacturing, 88, 102736.

[58] HURTADO E., BURGOS A., et al., 2025, *Self-Configurable Manufacturing Industrial Agents (SMIA): A Standardized Approach for Digitizing Manufacturing Assets*, Journal of Industrial Information Integration, Elsevier B.V., 47, https://www.scopus.com/inward/record.uri?eid=2-s2.0-105012948147&doi=10.1016%2Fj.jii.2025.100915&partnerID=40&md5=cdde1b533e3d477b13571cfe9339885b.

[59] KOSSE S., HAGEDORN P., et al., 2025, *Semantic Digital Twins in Construction: Developing a Modular System Reference Architecture Based on Information Containers*, Advanced Engineering Informatics, 67.

[60] SHI D., MEYER O., et al., 2025, *Dual Data Mapping with Fine-Tuned Large Language Models and Asset Administration Shells Toward Interoperable Knowledge Representation*, Robotics and Computer-Integrated Manufacturing, 91.