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Advancing the Collaboration in Manufacturing Networks – A Systematic Literature Review on Implementations of Asset Administration Shells and Data Spaces

Fabian Zink[a,*], Lorenz Fink[a], Bernhard Wallner[a], Friedrich Bleicher[a], Thomas Trautner[a]

[a] *Technische Universität Wien, Institute of Production Engineering and Photonic Technologies, Getreidemarkt 9, Objekt 1, BA -OG 8,1060 Wien, Austria*

* Corresponding author. Tel.: +43 1 58801 31128. *E-mail address:* zink@ift.at

Abstract

Collaboration in manufacturing networks is crucial to maximize the impact of digitalization and leveraging collected data. Addressing three key challenges – overcoming data silos, achieving semantic interoperability and protecting intellectual property – is essential. A promising solution is the combination of Asset Administration Shells and data space technologies. This systematic literature review investigates implementations of these two concepts in manufacturing, evaluating use cases based on their technological readiness levels and the technologies employed. The findings aim to guide researchers and practitioners and identify future research directions.

Keywords: semantic interoperability, data and service ecosystem, data space, asset administration shell, manufacturing, data sharing, collaboration, federated data infrastructure, Gaia-X, Digital Twin, Asset Administration Shell, ECLASS,

1. Introduction

The global volume of data has drastically increased in the past years and is set to further rise in the future. Especially in the manufacturing sector vast amounts of non-personal data are collected with a potential value estimated at € 1.5 trillion by 2027 [1]. Exploiting this manufacturing data holds tremendous potential for improving and optimizing manufacturing systems. Various use cases, such as circular economy, traceability, and condition monitoring, as outlined by the Factory-X initiative, can be implemented, enabling the achievement of broader objectives such as resilience and flexibility in supply and value chains [2].

The current state of the sector reflects significant progress in digital transformation. Companies have recognized the value of data, leading to the widespread introduction of Internet of Things (IoT) systems, the ubiquitous usage of sensors and smart devices, and the growing adoption of artificial intelligence (AI) and advanced analytics algorithms [3].

However, despite these advancements, the transformation is still ongoing and far from complete. To fully realize data-driven applications three key challenges must be addressed. First, the existence of heterogeneous, separate data silos lacking a standardized gateway for federated approaches [4] or lacking a holistic data integration must be overcome [5]. Originating from various data sources, such as sensors, control units and information systems like Manufacturing Execution Systems (MES) or Enterprise Resource Planning systems (ERP), structured, semi-structured and unstructured data is collected and stored separately. To deploy algorithms on all the data either the data must be integrated or standardized access points, that enable a federated deployment, defined.

The second challenge is to ensure semantic interoperability, i.e. the meaningful exchange of data between systems within manufacturing companies and across their value and supply chains [6].

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Third, the protection of intellectual property and manufacturing know-how embedded in data presents another challenge. A lack of trustworthiness between participants prevents the realization of the full potential of collaboration in manufacturing networks [7].

At present, no technology is widely available and sufficient to address and resolve these three challenges independently and on an industrial scale [8]. However, the combination of emerging technologies, such as federated data infrastructures and Asset Administration Shells (AAS), may offer a viable solution [9].

Although substantial research has been conducted on developing concepts for collaborative usage of data, a comprehensive analysis of practical implementations is missing. This systematic literature addresses this gap by identifying and critically evaluating implementations of these concepts in the manufacturing domain. The insights are evaluated and used technology approaches identified.

The rest of this paper is structured as follows: Section 2 lays the foundation and provides working definitions of key terms; Section 3 elaborates on the methodology of the systematic literature review, including the search strategy, search terms and strings; Section 4 presents the research questions and the results of the review. Section 5 concludes the review.

2. Key Terms

To properly search, identify and evaluate implementations of federal data infrastructures and AAS in a manufacturing context, key terms must be defined. The definitions have been identified in a preliminary study.

When considering large scale data sharing, three terms frequently come up: data space, federated data infrastructure and data ecosystem. Franklin et al. [10] explained how the concept of data spaces from of database management systems to avoid the significant upfront effort of data integration. Instead, data spaces have a co-existence approach and provide functionality across data sources [10]. The International Data Spaces Association has detailed how a dataspace looks like by defining three layers [11]. The business layer describes the participant role and how they interact with each other in the data space. The functional layer defines the functional requirements for the data space, among these are trust, security and data sovereignty, standardized interoperability, governance aspects. The third layer is the process layer, it specifies the interactions between components, main processes encompass the onboarding, the exchange of data and the publishing process [11].

Heimbigner and McLeod [12] coined the term federated database architecture in 1985. The authors have identified and described the basic problems of using integrated databases with a central authority. In a collaborative environment, participants are reluctant to hand over control over their data, furthermore the differences in conceptual structures, i.e. ontologies have been highlighted [12]. According to them a federated database architecture enables the sharing and exchange of information by loosely coupling components into a federation database. Thus, federated data infrastructures allow collaboration across different data spaces [12].

The third frequently used term is data ecosystem, also called data and service ecosystem. This system focuses on interdependent value creation. Nevertheless a widely accepted definition is missing [13]. As a working definition for this article, the ecosystems definition based on Strnadl and Schöning [14] is used. They define an ecosystem as an *"alignment structure of the multilateral set of partners that need to interact in order for a focal value proposition to materialize"* (Strnadl & Schöning, page 91, [14]). Consequently, a data ecosystem is such an ecosystem focused on data. Another noteworthy and interesting definition comes from Oliveira and Lóscio [15]. According to them a data ecosystem consists of autonomous actors, who consume, produce or provide data in a set of networks. Actors are interconnected and perform roles. Self-regulation of the system is achieved through a mix of collaboration and competition [15].

All three of these concepts are used often interchangeably and evolve constantly. To avoid confusion, the term "data infrastructure" is used in this article when referring to the general concept encompassing these three terms, rather than a specific one. The three specific terms have in common, that they mention some sort of governance, and consider the intellectual property and data safety aspect, although specific implementations differ.

Semantic interoperability can be achieved through different technologies, such as the previously mentioned AAS or alternatives. This is not to be confused with a semantic standardization of domain specific dictionaries, which is achieved via the integration of concepts such as ECLASS into the AAS.

The AAS concept originated in the Industry 4.0 initiative and is further developed by the Industrial Digital Twin (IDTA) Association [16]. Any physical or virtual entity can be represented through an AAS asset. An AAS asset is a standardized, digital representation of this entity in a machine-readable format [17]. There are three types of AAS interaction patterns. Passive AAS type 1 provides static data in the form of a file exchange. Reactive AAS type 2 provides an interface that allows access to dynamic data, e.g., via HTTP. Proactive AAS type 3 focuses on machine-to-machine communication and direct real-time data exchange [17]. A key aspect of the AAS asset is the submodel. It is a data model on a specific subject matter and is often standardized through templates [17]. For example, distinct machine tools are represented as AAS assets, each sharing a common submodel focused on energy usage, though the specific data varies between the machines. The integration of semantic identifiers, such as ECLASS, allows the vocabulary used, to be described in a widely recognized manner [18]. Generally, AAS provides a unified model that ensures consistent interpretation of data across applications and systems. by doing so it ensures semantic interoperability.

3. Methodology

The methodology follows established methods and approaches such as the ones from Cooper [19]. Figure 1 gives an overview of the search process, it is modeled after Heinz et al. [13]. The definition of the scope of this literature review follows Coopers notion. The review integrates a representative

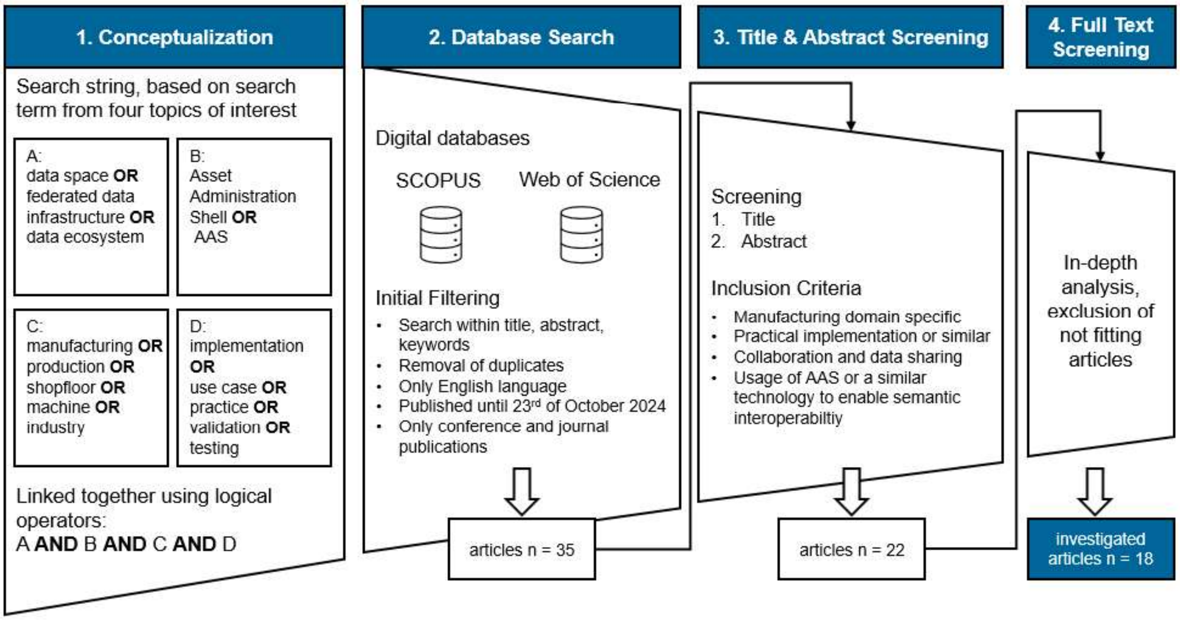

Fig. 1 Search strategy of the systematic literature review, modelled after Heinz et al. [14].

set of scientific publications that focus on applications that combine federated infrastructures and AAS. The goal is to synthesize, a representative set of literature with a neutral perspective, aiming to provide insights for both scholars and practitioners.

The conceptualization encompasses a preliminary study and the definition of key terms, as described in section 2. It starts out with collecting search terms, their synonyms and closely related words. These terms are grouped into four topics, to ensure a high precision in the literature search. Subsequently the search terms are combined using logical operators to one search string. This search string is entered into the two digital databases SCOPUS and Web of Science and an initial filtering is conducted. Within a screening process utilizing inclusion/exclusion criteria, only relevant articles are selected for the analysis. For the categorization and identification of contributions of the articles the concept-centric-view and approach as defined by Webster and Watson [20] is used.

4. Analysis

To guide the synthesis of the findings and systematically analyze them, the following research questions (RQ) are defined. The questions are based on the findings of the preliminary study.

- RQ1: What are the primary use cases for the implementation and what is their approximate Technology Readiness Level (TRL)?
- RQ2: Which AAS types, submodels and modeling tools are used?
- RQ3: Which domain standardization dictionary for the semantic understanding is employed?
- RQ4: Which data infrastructure technology stacks are used, and to what extent is Gaia-X adherence considered?
- RQ5: What challenges and limitations have been identified?

In the following analysis, each research question is addressed in turn, examining key concepts of the collected literature. It is important to note that some papers do not have the implementation as a focus, albeit their implementation approach is of relevance to the scope of this article.

RQ1: What are the primary use cases for the implementation and what is their approximate TRL?

The search strategy was set up specifically to generate results within the manufacturing domain. Nevertheless, within manufacturing, there are a multitude of different use cases and applications. Five clusters of use case foci are identified, with each use case assigned an estimated TRL. An overview of the assigned use cases is given in figure 2. It is important to note that the TRL assessment is approximate and provides only a rough indication of technological maturity. The TRL definition is based on the NASA Systems Engineering Processes and Requirements definitions [21]. The first cluster contains nine articles that focus on realizing digital twin applications, but do not specify the application in more depth.

Five of these articles are estimated to have a TRL of 2. They mostly focus on concept descriptions and do not test critical functionality and lack proof-of-concept implementation. The article from Redeker et al. [22] goes more in depth and fully models a shop floor for its case. This is regarded as a prototypical implementation and therefore assigned a TRL of 3. An extensive experimental case is developed and presented by Ding and Liu-qun which can be considered a breadboard validation in a laboratory environment and therefore TRL 4. The second cluster has two articles, both utilizing the two technologies to enable cognitive production, i.e., AI use cases. Iñigo et al. [23] present an extensive architecture for AI use cases, such as the sharing of machine learning models. Friedrich et al. [24] develop an approach to train federated machine learning models via data infrastructures. Both concepts are described in detail and the authors state that the implementation and validation experiments are in progress. Both articles focus on the formulation of technology concepts and applications, which corresponds to TRL 2.

The third cluster is called collaborative manufacturing, here, manufacturing resources are utilized together by more than one instance. One article describes an application for manufacturing as a service [25], the other one focuses on shared production [26]. Both focus on the conceptual application and therefore a TRL of 2 is assigned.

The fourth cluster sustainability incorporates two articles, both having a higher TRL. Volz et al. [27] develop a prototypical implementation leveraging the two technologies for storing product carbon footprints, TRL 3. Ajdinović et al. [28] write about Digital Product Passports (DPP) and validate the use case on an actual robot cell, resulting in TRL 4. Three further articles could not be sorted into the four clusters described above. Grüner et al. [29], investigate the application of AAS and data infrastructures in the context of process industries and identified valuable challenges hindering the usage, TRL 1. Alexopoulos et al. [30] investigated how AAS and data infrastructures can be applied to asses and improve manufacturing supply chain resilience. The authors describe the technological concepts and application in depth, which is in accordance with TRL 2. The highest score with regard to the TRL is achieved by Hang et al. [31]. Their focus is to implement the technologies to achieve an individualized production of juice beverages. The authors created their own software components and implemented it on an actual beverages manufacturing line [31]. This implementation can be described as a validation in a relevant environment and is therefore TRL 5.

In total there are nine levels of technological readiness [21]. Figure 2 visualizes the distribution among these levels. Not a single article goes beyond level 5. Most articles are part of basic technology research. Only the three highest ranking articles contribute to further technology development.

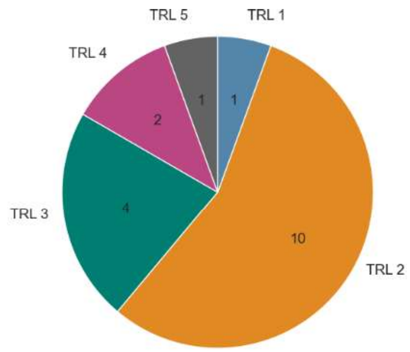

Fig. 2 Technological readiness of the investigated 18 articles.

RQ2: Which AAS types, submodels and modeling tools are used?

As explained in the key terms section, there are three AAS types. In their article published in 2023, Silva et al. [32] pointed out, that there is no available framework capable of implementing proactive AAS type 3. Furthermore, none of the other articles implements a proactive AAS type 3. Though, passive AAS type 1 and reactive AAS type 2 are mentioned and implemented to varying degrees in all articles. The IDTA metamodel, which provides the AAS details, provides only the high-level architecture and technical description of AAS. A certain software tool or approach is not specified or proposed explicitly [17]. Consequently, there is a multitude of different software tools, open source and proprietary that implement the AAS. Seven articles utilized the Eclipse AASX Package Explorer for visualizing their developed AAS models. Regarding the management and provision of repositories two tools came up frequently, the Eclipse BaSyx SDK and the Fraunhofer Advanced Asset Administration Shell Tools (FA^{3}ST). Seven articles utilize BaSyx, three implement FA^{3}ST. Volz et al. [27] further mention other approaches, such as the NOVA AAS, however, implement the FA^{3}ST framework due to its easier connectivity with OPC UA servers and Eclipse Dataspace Components (EDC). The authors Hang et al. [31] develop their own AAS deployment framework AASys. Furthermore, interesting in the context of AAS is the usage of submodels. Twelve articles mention to varying degrees that they developed their own submodels for their use cases. But only four articles used IDTA submodel templates. The most popular template is the digital nameplate template. Volz et al. [27] are using the product carbon footprint and the digital nameplate templates. The digital nameplate and technical details templates are used by Iñigo et al. [25] and Dickopf et al. [33]. Grüner et al. [29] are investigating and discussing a larger number of templates and their fit to their use case. Furthermore, these authors mention that additionally to the basic information in the IDTA templates, further submodels must be developed for their use cases. Not exactly AAS specific, are the tools used to connect the AAS with the manufacturing assets. Concerning the machine connectivity, six articles propose the usage of MQTT and eleven OPC UA. Note, some articles put forward both technologies.

RQ3: Which domain standardization dictionary for the semantic understanding is employed?

An important aspect of the AAS are the semantic identifiers that standardize the dictionary used. The Industry 4.0 Language (I4.0L) to be fully utilized for the proactive AAS type 3, is mentioned in two articles. The ECLASS is referenced six times, the International Electrotechnical Commission Common Data Dictionary (IEC CDD) is connected to the AAS five times. The article by Yallıç and Albayrak further mentions the identification scheme by the industrial automation systems and integration technical specification (ISO/TS 29002-5) [34]. A more in-depth analysis of the need for standardization of the AAS files is conducted by Grüner et al. [29] who also propose AutomationML and other specific frameworks, some also put forward to be implemented with a submodel, such as DEXPI, a standard for the data exchange in the process industry.

RQ4: Which data infrastructure technology stacks are used, and to what extent is Gaia-X adherence considered?

This question aims to identify the technology used to create the data infrastructure, e.g., data spaces. The most frequently applied technology is the International Data Spaces components, which are developed by the International Data Space Association. Nine articles are using IDS components. Especially Hang et al. [31] use the IDS connector as a basis and further extensively elaborate on the implementation of their data infrastructure. Four articles are using the EDC. Worthwhile mentioning, is the article by Volz et al. [27] connecting Fa^{3}st with EDC and showing how a user interface could look like. Another three articles are implementing use cases with their own developments. For example, Ding and Liu-qun developed their own blockchain based ecosystem,

Table 1 Overview of reviewed literature

Title	Author	Year	Citation
A Digital Twin Platform-Based Approach to Product Lifecycle Management: Towards a Transformer 4.0	Silva et al.	2023	[32]
An approach for Industrie 4.0-compliant and data-sovereign Digital Twins Realization of the Industrie 4.0 Asset Administration Shell with a data-sovereignty extension	Jacoby et al.	2021	[35]
An industrial data-spaces framework for resilient manufacturing value chains	Alexopoulos et al.	2023	[30]
Application of the Asset Administration Shell in the context of Engineering Data Management Systems	Dickopf et al.	2023	[33]
Architecture design and prototype system development: Blockchain-driven D&A Interoperability implementation based on AAS-Work-Centre	Ding and Liu-qun	2023	[36]
Architecture for Shared Production Leveraging Asset Administration Shell and Gaia-X	Jungbluth et al.	2023	[26]
Asset Administration Shell Generation and Usage for Digital Twins: A Case Study for Non-destructive Testing	Yallıç and Albayrak	2022	[34]
Constructing a Real-Time Value-Chain Integration Architecture for Mass Individualized Juice Production,	Hang et al.	2022	[31]
Enabling Federated Learning Services using OPC UA, Linked Data and Gaia-X in Cognitive Production	Friedrich et al.	2024	[24]
FA3ST Service - An Open Source Implementation of the Reactive Asset Administration Shell	Jacoby et al.	2022	[37]
Interoperable Digital Product Passports: An Event-Based Approach to Aggregate Production Data to Improve Sustainability and Transparency in the Manufacturing Industry	Ajdinović et al.	2024	[28]
Manufacturing system under I4.0 workshop based on blockchain: Research on architecture, operation mechanism and key technologies	Ding et al.	2021	[38]
On the Role of Digital Twins in Data Spaces	Volz et al.	2023	[27]
Towards an Advanced Artificial Intelligence Architecture Through Asset Administration Shell and Industrial Data Spaces	Iñigo et al.	2023	[23]
Towards an Autonomous Application of Smart Services in Industry 4.0	Redeker et al.	2021	[22]
Towards asset administration shell-based continuous engineering in process industries	Grüner et al.	2023	[29]
Towards integrated data control for digital twins in industry 4.0	Bader and Maleshkova	2020	[39]
Towards Standardized Manufacturing as a Service through Asset Administration Shell and International Data Spaces Connectors	Iñigo et al.	2022	[25]

which falls into the category of data infrastructures, without using any predeveloped technology [36]. Three articles do not implement data infrastructure technology. However, these articles show an interesting application of the AAS and are therefore part of the analysis. While most studies state the data infrastructure technology and some even publish data in such a space, comprehensive descriptions of the integration depth and testing are mostly lacking. A preliminary foundation has been set, yet further empirical studies are needed to advance.

Some also express alignment with Gaia-X principles. However, the specific role and relevance of Gaia-X in these implementations often remain unclear, suggesting a need for greater clarity of its practical contributions and applicability in both research and real-world implementations. This ambiguity might reflect broader challenges in articulating Gaia-X's framework and its implications within the manufacturing context.

RQ5: What challenges, lessons learned, and limitations have been identified?

Most articles propose concepts and technology architectures and only a few of them implement prototypes of their use cases. This is reflected in the low technological readiness, where most articles are considered basic technology research. Due to the limited implementation of use cases, there is a lack of practical experience and insufficient stakeholder feedback. However, some challenges have been identified. One challenge identified by Ajdinović et al. [28] is that companies lack adequate digital infrastructure to implement the new technologies. Challenges in implementing AAS have been identified by Grüner et al. [29]. The AAS technology has currently no version control, neither regarding the content nor the submodel generation in use [29]. Furthermore, the scalability in employing AAS for systems and sub-systems might become an issue, due the size of the networks and the resulting increase in synchronization time and computational resource need [26].

Regarding the data infrastructure, Hang et al. [31] identified the data infrastructure portal as a single point of failure. Any implementation running via such a portal, stops when the portal crashes. Jungbluth et al. [26] stated that legal agreements between participants are needed to ensure that the data usage follows the agreed and committed conditions.

5. Conclusion

This systematic literature review assessed the state of implementations combining AAS and data infrastructures in manufacturing. An analysis based on five RQs revealed the direction for future research to overcome barriers preventing widespread adoption. Researchers must shift from concept development to real-world implementations to increase the solutions' TRL. Additionally, defining objectives simply as "creating a digital twin" is often too broad, hindering the level of detail needed for impactful outcomes. Addressing specific manufacturing use cases, such as DPP might prove useful. Furthermore, the three terms data space, federated data infrastructure and data and service ecosystem, need to be clearly defined and distinguished. Moreover, for each of these terms, a differentiation must be made between the scientific concept of it and the practical realization. By clarifying the theory and increasing the TRL, the technical barriers for integrating these concepts can be overcome. Increasing the TRL is expected to lead to the crystallization and widespread adoption of viable technical approaches. Regulatory and financial barriers may also emerge later, but the technical barriers are currently the most important to overcome. A major limitation of this review is the small number of scientific publications analyzed.

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