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Review article

Understanding data spaces: A Systematic Mapping Study of foundations, technical building blocks, and sectoral adoption

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ABSTRACT

Data spaces are emerging as a key paradigm for enabling sovereign, secure, and interoperable data sharing across sectors. Beyond data governance, they represent a transformation in communication architectures—where communication is no longer merely about establishing connections, but about *who is allowed to share what, under which conditions, and for what purpose*. Despite growing attention, the research landscape remains fragmented and under-synthesized. This paper presents a Systematic Mapping Study (SMS) of 149 peer-reviewed publications, analyzing the conceptual foundations, technical building blocks, and sectoral adoption of data spaces. Following established SMS methodologies, we classify the literature across key technical themes defined by the Data Spaces Support Centre (DSSC) and assess methodological maturity, technical novelty, and application domains. Our findings show that 46.3% of studies address data value creation enablers, 30.8% focus on data interoperability, and 22.9% explore data sovereignty. The study provides a structured synthesis of current research and offers guidance for advancing federated, trust-aware communication infrastructures.

Contents

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1. Introduction

The growing demand for sovereign, secure, and interoperable data sharing across organizations and sectors has led to the emergence of data spaces [1]—decentralized infrastructures that enable controlled data exchange while preserving data ownership, usage policies, and trust mechanisms [2–4].

Initially pioneered through European initiatives such as the European Strategy for Data [5], and now gaining international momentum, data spaces represent more than a shift in data governance. They also signify a transformation in communication architectures—where communication is no longer merely about establishing connections, but about *who is allowed to share what, under which conditions, and for what purpose*.

The growing impact of this paradigm is evident in its adoption across domains, including manufacturing [6,7], healthcare [8], mobility [9,10], agriculture [11–13], tourism [14,15], and energy [16,17]. These examples highlight the versatility of data space principles and their role in reshaping communication infrastructures into trust-aware, policy-driven, and context-sensitive ecosystems.

To enable this transformation, reference architectures such as those developed by the International Data Spaces Association (IDSA) [2,18] and Gaia-X [19] provide technical foundations for interoperability, sovereignty, trust, and scalable value creation [20,21]. The Data Spaces Support Centre (DSSC) complements these efforts with a detailed blueprint outlining the business, organizational, and technical building blocks necessary for cross-sectoral implementation [22].

Despite the growing interest in data space research, the field exhibits significant fragmentation with diverse implementation approaches and varying maturity across domains. Although reference architectures define coherent sets of core components, there is no systematic, evidence-based analysis of how these elements are being addressed in academic literature, implemented in practice, or integrated across technical layers. This lack of synthesis creates barriers for researchers, practitioners, and policymakers.

To address this gap, **we conduct a Systematic Mapping Study (SMS) to thoroughly analyze, classify and clarify the current body of research on data spaces**, supporting researchers in identifying directions for future work while enabling practitioners to navigate existing approaches and inform implementation strategies.

This SMS provides a comprehensive overview of data space research, examining conceptual frameworks, technical implementations, and sector-specific applications. We systematically categorize the literature to identify progress in key technical building blocks — data interoperability, sovereignty, and value creation — while assessing research maturity across implementations, offering a structured reference that highlights both established practices and areas requiring further development. To the best of our knowledge, this is the most comprehensive and up-to-date SMS on data spaces, analyzing 149 primary studies published up to April 2025.

Following established methodologies for evidence-based literature categorization [23,24], we exhaustively analyze these studies according to six Research Question (RQ):

- RQ1: What is the methodological maturity and technical novelty of data space research, and how has it evolved?
- RQ2: What is the coverage, evolution, and interrelation of technical building blocks in data space research?
- RQ3: What is the coverage, technical novelty, and interrelation of data interoperability in data space research?
- RQ4: What is the coverage, technical novelty, and interrelation of data sovereignty in data space research?
- RQ5: What is the coverage, technical novelty, and interrelation of data value creation enablers in data space research?
- RQ6: Which sectors received most attention and how is this attention evolving?

RQ1 provides insights into the methodological rigor and innovation trajectory of data space research, revealing whether the field is predominantly conceptual or has progressed to validation and evaluation stages. RQ2 examines the landscape of technical building blocks, identifying coverage patterns and interdependencies that form the foundation of data space implementations. RQs 3–5 delve into specific building blocks—data interoperability (RQ3), data sovereignty (RQ4), and value creation enablers (RQ5)—analyzing their technical advancements, interconnections, and implementation approaches. These questions examine "how" data spaces are constructed technically, while RQ6 addresses "where" they are applied, mapping sector-specific implementations and adoption trends. Collectively, these questions identify research hotspots, technical gaps, and emerging patterns to guide future data space development across domains. Additionally, we outline a brief for each of the 149 primary studies, offering a systematic classification and summary of their contributions to facilitate navigation of the data space research landscape.

The remainder of this paper is structured as follows. Section 2 introduces the concept of data spaces, outlining initiatives and key components. Section 3 describes the research methodology, detailing the phases and decisions of the SMS process. It also identifies the novelty of our work and compares it with related secondary studies. Section 4 presents the categorization of primary studies, followed by a detailed analysis in Section 5. The paper concludes in Section 6, summarizing the main findings.

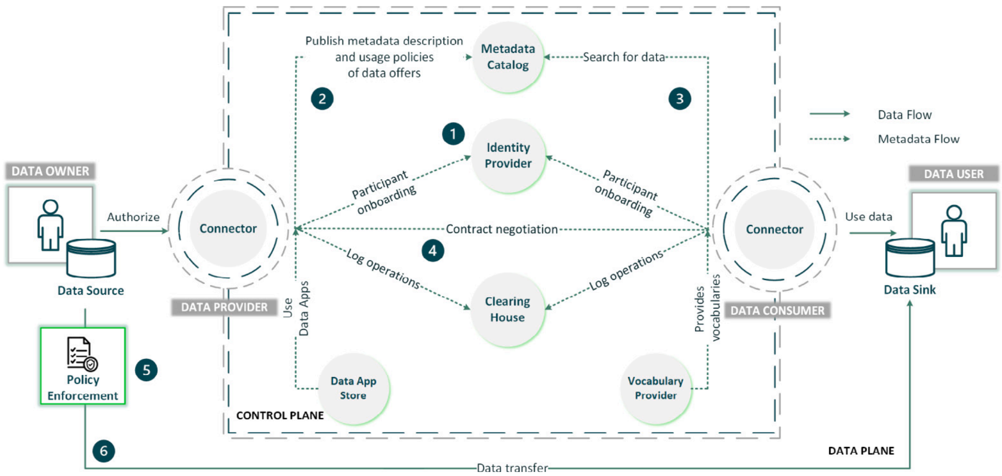

Fig. 1. Data space reference architecture, participating roles and core processes, based on [2,30].

2. Background

This section introduces data space fundamentals, including reference architecture principles and building blocks, providing the conceptual foundation that guides our SMS.

2.1. Foundations and context of data spaces

Concept and evolution: The concept of data spaces has evolved from early data management abstractions to today's comprehensive frameworks for sovereign data exchange [25]. While Franklin et al. [26] introduced "dataspaces" in 2005 as an approach for managing heterogeneous data sources, modern data spaces represent a fundamentally different paradigm. The DSSC defines contemporary data spaces as "*interoperable frameworks based on common governance principles, standards, practices and enabling services, that enable trusted data transactions between participants*" [22].

Data spaces gained prominence through European initiatives, beginning with the Industrial Data Space by Fraunhofer in 2014 and the subsequent founding of the IDSA in 2016 [2,18]. The European Strategy for Data [5] (2020) accelerated adoption by promoting sectoral data spaces and laying the groundwork for subsequent regulatory frameworks, such as the Data Governance Act [27] and Data Act [28].

Other initiatives include Gaia-X [19], which enhances data spaces with federated cloud services, FIWARE providing open-source components, the DSSC coordinating common building blocks [22], and the Data Spaces Business Alliance (DSBA) focusing on business adoption and technical convergence [20]. Moreover, Smart Open-source Middleware (SIMPL)[1] represents a recent European initiative developing middleware to bridge existing data space implementations.

[1] https://digital-strategy.ec.europa.eu/en/policies/simpl.

Table 1
Comparing data spaces with other data management approaches.
Source: Adapted from [29].

Aspect	Traditional systems[a]	Data spaces
Architecture	Mostly centralized	Distributed
Data control	Limited or transferred	Sovereign
Schema	Rigid	Semantic interoperability
Governance	System-defined	Federated
Usage control	Limited, system-level	Fine-grained, policy-based
Scope	Data management	Data ecosystems
Scale	Organizational	Cross-organizational

[a] Including data lakes, warehouses, and conventional federated databases.

To clarify the distinctive characteristics of data spaces, Table 1 compares them with traditional data management approaches. Conventional systems typically prioritize centralized control and predefined schemas, requiring data owners to surrender control when sharing. In contrast, data spaces enable cross-organizational collaboration without transferring data ownership, combining decentralized architecture with sovereignty-preserving mechanisms. Rather than merely storing or processing data, data spaces create ecosystems where data can flow freely while remaining under the data owners' control.

Architectural principles: Data spaces are based on a decentralized architecture comprising several key roles: data owners who maintain legal rights to the data, data providers who technically contribute and control assets (often the same entity as owners), data consumers who utilize these assets, and intermediaries such as catalog providers that facilitate asset discovery. These interactions are structured through two distinct planes: the control plane — which handles participant onboarding, resource cataloging, and contract negotiation — and the data plane, where actual data exchange occurs.

Fig. 1 illustrates these roles and planes. This ecosystem operates through a set of core processes [2,31]: (1) participant onboarding with identity verification, (2) data asset descriptions and usage policies specification, (3) data discovery and catalog search, (4) contract negotiation, (5) policy enforcement, and (6) data transfer according to agreed terms.

To support these processes, distinct reference architectures have emerged. The International Data Spaces (IDS) Reference Architecture Model (RAM) defines conceptual components for data spaces [2,18], while Gaia-X provides an alternative architecture focused on federating cloud services [19].

These architectural principles and core processes are realized through connectors [32], with major open-source implementations [33] including the Data Space Connector (DSC) [34], Trusted Connector [35], TRUE Connector [36], and the Eclipse Dataspace Components (EDC) [30], which increasingly adopt standardized protocols like the Dataspace Protocol (DSP) [31] to enable consistent cross-connector interactions.

2.2. DSSC technical building blocks

The DSSC Blueprint [22] categorizes data spaces building blocks into business, organizational, and technical components. As part of our SMS, we focus on the technical building blocks that form the foundation of functional data spaces. These are structured into three categories:

- **Data interoperability** facilitates consistent data sharing through shared semantic models, standard exchange protocols, and lineage tracking systems.

- **Data sovereignty and trust** secures the data space by identifying participants, components, and assets, while enforcing trust measures and usage policies.
- **Data value creation** encompasses registering data offerings, publishing and discovering data, and establishing marketplaces for data and services.

3. Methodology

A SMS is an evidence-based secondary study that provides a research area overview by identifying, categorizing, and analyzing existing literature to uncover evidence, gaps, and trends. SMSs help to guide new research, prevent duplication, and identify areas for deeper Systematic Literature Review (SLR) analysis. Following guidelines and procedures for undertaking SMSs [24,37,38], our methodology comprises three phases, as shown in Fig. 2:

- *Planning the review*: Setting the review need, RQs, and related literature assessment. We complement Petersen et al. [24]'s approach with a protocol definition process and the data collection form as suggested in [23].
- *Study identification*: Identifying relevant papers through digital database queries, then filtering based on inclusion/exclusion criteria to yield primary studies.
- *Data extraction and classification*: Analyzing primary studies to derive the classification schema and categorizing studies accordingly.

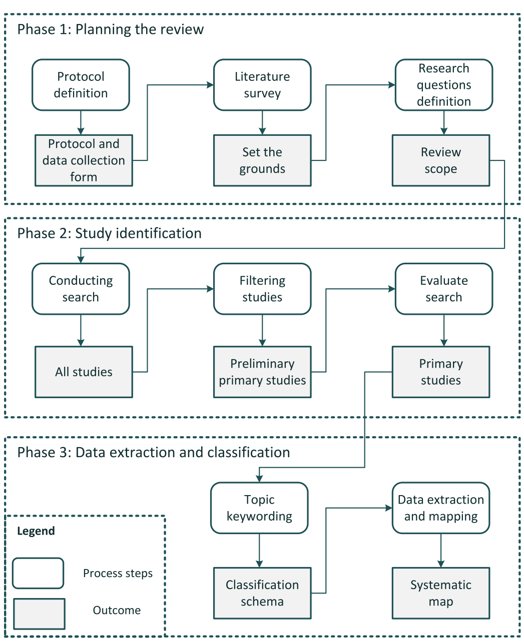

Fig. 2. SMS methodology process.
Source: Adapted from [24].

3.1. Phase 1: Planning the review

This section outlines our SMS planning process, adhering to the methodology proposed by Kitchenham et al. [23]. The planning phase comprises three interrelated activities: (1) *protocol definition*, (2) *literature survey*, and (3) *RQ formulation*. Since we have already presented the RQ1–RQ6 in Section 1, we focus here on explaining how we defined our search protocol and conducted the literature survey.

3.1.1. Protocol definition

The protocol defines the need for the review, the topic, scope, preliminary RQs, search strategy, selection criteria, and data extraction form [23]. We iteratively reviewed and refined this protocol throughout the process.

The need for the review: This SMS responds to the necessity to systematically map out data space research to identify trends, focal points, and gaps. The study also identifies leading publication venues and geographical centers of innovations to clarify where and how data spaces are being advanced, providing context for researchers and practitioners navigating the field. Sections 1 and 2 complement this mapping, providing an overview of data spaces and its distinctive concerns.

Preliminary RQs: The goal of this study was to obtain a comprehensive overview of current research on data spaces.

The search strategy: Our approach ensures the inclusion of relevant papers and the exclusion of irrelevant ones through digital database queries with customized search strings, followed by manual filtering using predefined criteria. This process is detailed in Section 3.2.

Inclusion and exclusion criteria: We formulated the following Inclusion Criteria (IC) and Exclusion Criteria (EC) to systematically filter the studies. The IC are:

- IC1: The study focuses on data spaces (as defined by DSSC [22]) or explicitly states that the proposed solution is intended to be implemented in data spaces.
- IC2: The study addresses at least one technical building block as defined by DSSC [22], focusing on technical aspects rather than solely on governance or business aspects.
- IC3: The study is peer-reviewed.

Complementarily, we defined the following EC:

- EC1: The study mentions data spaces only incidentally rather than as a central focus.
- EC2: The study uses the term "data space" in a context misaligned with the DSSC definition.
- EC3: The study focuses exclusively on governance or business aspects of data spaces.
- EC4: The study is gray literature, an introduction/keynote, a secondary study, an extended abstract, tutorial, review, or book chapter without original technical contribution.
- EC5: The study is an earlier or less comprehensive version of research that is more completely presented in another paper already included in the review.
- EC6: The study is in a language other than English.

Data extraction form: To collect all the information needed to address the RQs, record rationales for IC and EC, and classify the studies along the classification schema, we developed a structured data extraction form represented in both spreadsheet and JSON formats. In these forms, we collect all metadata of the studies (title, authors, year, publication type, venue, abstract, keywords) and classification details. **The resulting dataset of primary studies is available in our repository.**[2]

3.1.2. Literature survey

Table 2 lists existing secondary studies that review data space literature. While previous studies also target taxonomies and specific technologies [39–41], this SMS addresses a broader research gap by comprehensively assessing coverage, maturity, and evolution patterns across the entire data space field using the DSSC technical building blocks framework [22].

[2] https://github.com/anhelinakovach/data-spaces-systematic-mapping.

Table 2
Comparison of existing secondary studies on data spaces, addressing topics, coverage and RQs.

Reference	Year	Topic	Coverage	Research questions
Gieß et al. [39]	2025	Data space disambiguation and different design options	Apr. 2022	(i) What are the key characteristics to describe and classify data spaces? (ii) How to (re)design data spaces?
Bacco et al. [40]	2024	Data space disambiguation and technology support	2018–2023	(i) What are data spaces? (ii) How do data spaces work? (iii) What components are presently available and what are the expected developments in the future?
Otsu and Maso [42]	2024	DTs for the European GDDS	Jan. 2024	Not explicited in the paper: (i) What is the relationship between DTs and data spaces? (ii) What are existing technical gaps for the GDDS?
Singh et al. [41]	2024	Convergence of IoT, AI and DLTs supporting data space at the edge	2017–2022	(i) How are Blockchain/DLT, IoT, AI, and Edge Computing being used in combination? (ii) What are the relevant challenges to integrating these technologies at edge for dataspace applications?
Hauff et al. [43]	2024	Semantics for FAIR compliance	Feb. 2024	(i) How can semantics contribute to FAIR compliance in dataspaces?
Stäbler et al. [44]	2024	Semantic interoperability	Not specified	(i) How can tools be designed for automatable, scalable, and resilient semantic interoperability within and across data spaces?
Oliveira et al. [45]	2024	Gaps of legal interoperability	Not specified	(i) What is legal interoperability in data spaces? (ii) What is the conceptual relationship between data sovereignty and legal interoperability regarding IDS? (iii) What is the current representation of legal moments in data/usage policies within IDS and related data ecosystems? (iv) What are the legal challenges within the IDS domain? (v) Are there gaps and opportunities for research and development regarding the legal aspect of IDS?
Czvetkó and Abonyi [46]	2023	Data sharing in Industry 4.0	2022	(i) What are the major application fields of AutomationML and B2MML? (ii) Which technologies support/rely on the application of these data models? (iii) How have these models been extended? (iv) How can standard data models promote horizontal integration and the digital data ecosystem? (v) Which inter-organizational challenges can be solved by the International Data Spaces concept?
This work	–	Data space disambiguation and coverage of technical aspects	2016–2025	See RQs in Section 1

In this sense, this SMS classified 149 primary studies published up to April 2025 and differs from existing work by providing: (1) a significantly broader corpus, with 111 more studies than the most comprehensive prior review [40]; (2) a classification grounded in DSSC building blocks, aligning academic research with industrial implementation needs; (3) a combined assessment of technical coverage and implementation maturity, highlighting both theoretical innovation and practical readiness; and (4) a comprehensive thematic analysis (Section 4) which maps the technical landscape in an accessible and structured way, highlights emerging trends, and uncovers interrelations among technical building blocks, offering readers a clearer understanding of how the field is evolving.

3.2. Phase 2: Study identification

Fig. 3 depicts the process followed in this phase, which includes *conducting the search*, *filtering studies* and an additional *evaluating the search* step to verify and provide rigor.

3.2.1. Conducting the search

In this step, the focus is on constructing an effective search string to query digital databases. Notably, the term "data space" is frequently used interchangeably with "dataspace", so both variations are included in our search criteria. This approach ensures that the search captures a broad range of relevant studies and implementations.

$$TITLE\text{-}ABS\text{-}KEY \ (\text{"}data\ spaces\text{"}\ OR\ \text{"}dataspaces\text{"}\ OR\ \text{"}dataspace\text{"}\ OR\ \text{"}data\ space\text{"})\ AND\ PUBYEAR > 2016$$

To ensure relevance and applicability, we limited our search to studies published **from 2016 onward**. This decision is based on two factors. First, during this period, major advances in data technologies such as big data, cloud computing, and data integration laid the groundwork for today's data space concept. Second, key initiatives (e.g., IDSA (founded in 2016), Gaia-X (initiated in 2019)) emerged during this timeframe.

We restricted the search to studies published **up to April 2025**. The following electronic databases were consulted: IEEE Xplore,[3] ACM Digital Library,[4] Springer Link,[5] Science Direct,[6] MDPI[7] and Wiley Online Library.[8] The search query was matched against the title, abstract, and keywords. Fig. 3 details the process, from initial search to final selection.

From our search across these databases, a total of 2,136 potential studies were identified. Notably, IEEE Xplore returned the highest number of studies (43.3%), followed by Science Direct (27.8%) and MDPI (12.7%). The remaining studies were distributed across Springer Link (7.3%), ACM (8.5%), Wiley (0.3%), and manually retrieved studies (0.1%). After removing 11 duplicates, 2125 studies remained.

3.2.2. Filtering studies

We filtered papers according to the IC and EC from Section 3.1.1, including only papers meeting all IC and no EC. Although filtering was conducted primarily by one researcher, uncertain cases were resolved through team discussion, with key filtering debates including:

- EC1 ("The study is not centered on data spaces"): We found that some studies mentioned data spaces only peripherally rather than as their primary focus. For instance, some studies just mentioned data spaces in related work (e.g., [47]), future lines (e.g., [48,49]), or compare their proposed solution to data spaces (e.g., [50]).
- EC2 ("The study uses misaligned terminology"): Some studies use searched terms but are not aligned with the DSSC concept. Misaligned terminology includes papers on: (1) mathematical

[3] http://ieeexplore.ieee.org/.
[4] http://dl.acm.org/.
[5] http://link.springer.com/.
[6] http://www.sciencedirect.com/.
[7] https://www.mdpi.com/.
[8] https://onlinelibrary.wiley.com/.

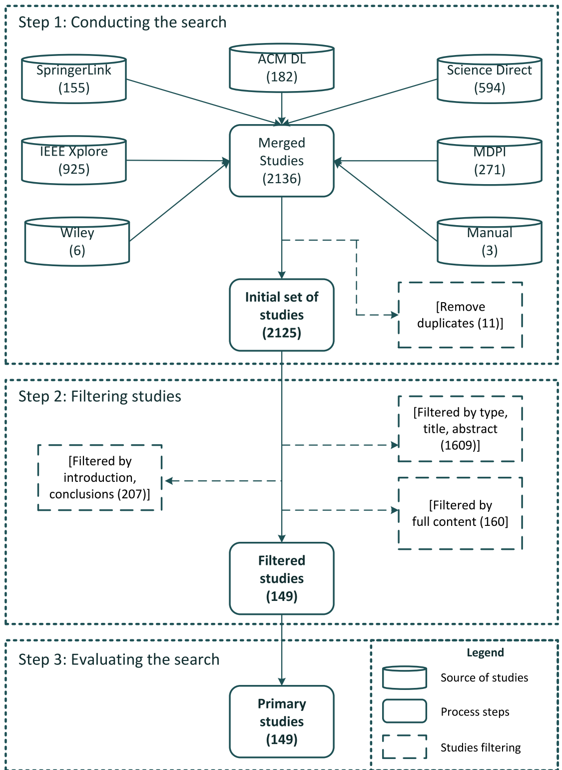

Fig. 3. Study identification process.

approaches for data vectors (e.g., [51,52]), (2) computer vision applications (e.g., [53,54]) or (3) early data integration abstractions "dataspace" concept [26] (e.g., [55–57]).

- EC3 ("The study focuses on non-technical aspects"): Several studies addressed data spaces from just governance, business model, or organizational perspectives. For instance, some papers focused exclusively on legal frameworks (e.g., [58]), data space business models (e.g., [59]), or organizational governance structures (e.g., [60]).
- EC4 ("The study is gray literature"): We excluded gray literature, keynotes, abstracts, tutorials, surveys, reviews, and book chapters (e.g., [61–64]).
- EC5 ("Related versions"): We included the most comprehensive and recent version while excluding preliminary variants (e.g., [14,65–67]).

We applied a three-stage filtering process to the initial set of studies (see Fig. 3 Step 2). Filter 1 examined titles and abstracts, Filter 2 reviewed introductions and conclusions, and lastly, Filter 3 analyzed the full content. At each stage, studies were only excluded when they met EC and failed to meet IC; when uncertain, we advanced papers to the next stage. For studies reaching the third stage, all researchers reached consensus through discussion. This process yielded 149 primary studies.

3.2.3. Evaluating the search

One researcher meticulously conducted the filtering process following a broad search strategy, employing an extensive search string that encompassed all terminology and concepts related to data spaces.

3.3. Phase 3: Data extraction and classification

This phase comprises *relevant topic keywording* and *data extraction and mapping* iterative tasks (see Fig. 2 Phase 3).

3.3.1. Relevant topic keywording

This process yielded our classification schema, which includes four facets: *Building Blocks*, *Research Type*, *Technical Novelty*, and *Sector*.

The classification schema is grounded in the literature. Specifically, we performed the *relevant topic keywording* process to refine the *Building Blocks* facet, starting with the coarse-grained classification proposed by DSSC [22]. During this process, a reviewer read each paper and identified keywords and concepts that reflected their contributions. These keywords were then combined and clustered to form fine-grained categories within the *Building Blocks* facet. The resulting detailed schema is presented in Section 4 as part of the mapping of primary studies.

Facet 1: Building Blocks. This facet identifies which core technological components a study focuses on when contributing to data spaces. The classification schema aligns with the technical building blocks defined by DSSC Blueprint:

- *Data Interoperability* studies focus on capabilities needed for effective data exchange, including *Data Models*, *Data Exchange*, and *Provenance and Traceability*. These components enable semantic understanding, exchange protocols, and tracking of data lineage.
- *Data Sovereignty* studies focus on capabilities needed for identifying participants and assets in a data space, establishing trust, and defining and enforcing policies for access and usage control. This includes *Identity Management*, *Trust Framework*, and *Usage Control*.
- *Data Value Creation Enablers* studies focus on capabilities that enable value creation in a data space, including *Data Offering*, *Publication and Discovery*, and *Value Creation Services* that facilitate registration, discovery, and utilization of data assets.

Each study is classified into one or more technical building blocks based on its primary focus. This facet serves as an indicator for actionable research by identifying which aspects of data spaces are being regarded and disregarded.

Facet 2: Research Type. The facet reflects the research approach used in the primary study. Research type categories are based on the scheme proposed by Wieringa et al. [68].

- *Opinion Paper* expresses subjective viewpoints on approaches or methodologies without empirical validation.
- *Experience Paper* explains what and how something has been done in practice, based on the personal experience of the authors, typically from industry settings.
- *Conceptual Paper* introduces frameworks that offer new perspectives on existing domains.
- *Solution Proposal* presents novel approaches or significant extensions to existing techniques, validated through limited demonstration or argumentation.
- *Validation Research* tests proposed solutions through controlled experimentation before practical implementation.
- *Evaluation Research* assesses implemented techniques in real-world environments, analyzing both application methods and consequent benefits and limitations.

Studies are classified into a single research type category. When a study fits multiple categories (e.g., both solution and validation), we assign the category with the highest maturity according to the following descending order: *Evaluation Research* (highest), *Validation Research*, *Solution Proposal*, *Conceptual Paper*, *Experience Paper*, and *Opinion Paper* (lowest). This ranking reflects research maturity, with evaluation studies demonstrating the highest maturity through real-world implementation assessment, whereas opinion and conceptual papers typically indicate emerging research areas.

Notably, the existing classification schema does not differentiate between studies that introduce novel technical contributions versus those that integrate existing technologies. This distinction is crucial because data spaces emphasize reusing proven technologies [2]. To address this gap, we introduce the *Technical Novelty* facet (see next).

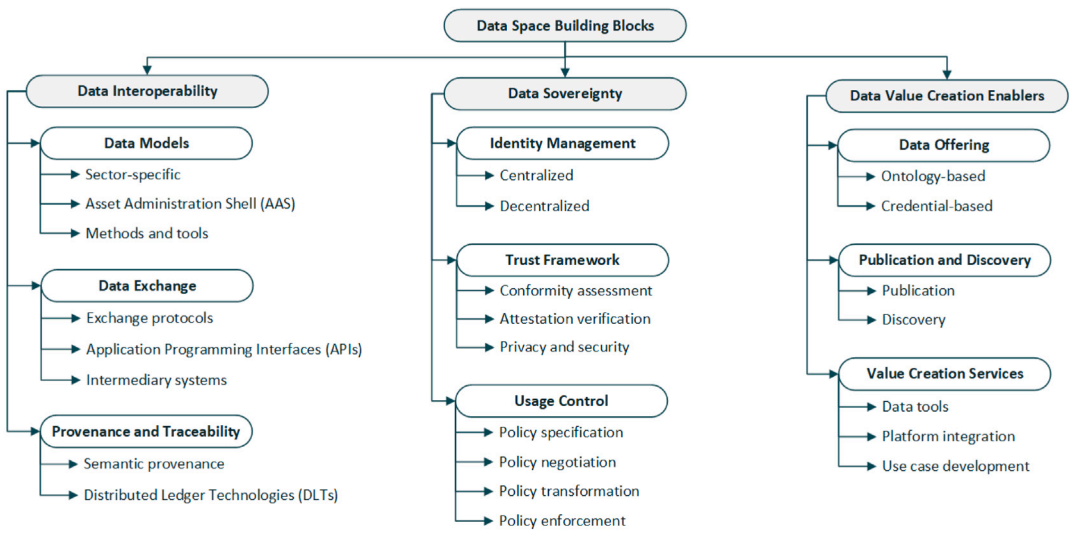

Fig. 4. Refined classification framework for *Facet 1 - Building Blocks*: extending from DSSC [22].

Facet 3: Technical Novelty. This facet distinguishes between studies implementing existing architectures and those introducing new technological contributions:

- *Reuse and Integration* studies apply and adapt existing technologies to build data space solutions, demonstrating an effective combination of current tools and frameworks.
- *Novel Approach* studies introduce fundamentally new techniques, methodologies, or tools that significantly depart from existing approaches, focusing on innovation rather than direct implementation.
- *NA* (Not Applicable) indicates insufficient information to determine technical novelty or studies where technical development is not addressed.

This facet interacts with *Facet 1 - Building Blocks* as each building block addressed in a study is assigned to a single *Technical Novelty* category. Additionally, it complements *Facet 2 - Research Type*, distinguishing between studies advancing technical innovation and those reusing technologies.

Facet 4: Sector. The facet classifies studies based on their application area, helping to understand how data space technologies are being applied across different sectors. The classification schema follows Common European Data Spaces [5].[9] This classification assigns each study to a single distinct category. It is crucial because data spaces are often designed and deployed for specific sectors such as healthcare or tourism.

3.3.2. Data extraction and mapping

Primary studies were sorted according to the classification schema, which evolved during extraction, with categories added, merged, or split as needed. One reviewer populated the extraction form with a brief description of each paper's contribution, classified the study into four facets, and provided a rationale for its placement. Other reviewers verified the outcomes, and discrepancies were resolved through a full reassessment until a consensus was reached. This was the case of 45 papers. The mapping of primary studies and their brief is provided in Section 4.

[9] https://digital-strategy.ec.europa.eu/en/policies/data-spaces.

3.4. Threats to validity

The validity of SMS outcomes may be threatened by selection bias and extraction and classification errors [69].

3.4.1. Selection of studies

To mitigate bias from nonstandardized terminology in data spaces, we refined our search strategy by consulting keywords from related mapping studies and performing a pilot search to assess keyword noise. Searches were conducted in major scientific databases (ACM, IEEE Xplore, Springer, ScienceDirect) with 11 duplicate papers identified and removed. Strict IC and EC were applied to ensure transparency. Studies with ambiguous classification underwent a review from abstract to full text by all researchers, leading to the reconsideration of 45 studies.

Although a formal quality scoring system was not applied, our exclusion criteria filtered out lower-quality publications (e.g., gray literature, keynotes). The chosen databases (ACM, IEEE Xplore, Science Direct, Springer Link, Wiley) are widely recognized as reliable sources in the research community.

Our study focuses exclusively on data spaces. Hence, we did not examine if broader research topics might be applicable.

3.4.2. Classification errors

To mitigate bias during data extraction, one researcher performed the initial extraction and classification. In cases of disagreement, the full text was reevaluated until a consensus between all researchers was reached. This process was necessary for 45 papers.

4. Mapping of primary studies

This section summarizes the primary studies, which required a thorough examination of their full content to explore the *Facet 1 - Building Blocks* across architectural, technological, and implementation dimensions. As shown in Fig. 4, we examine and adapt the DSSC building blocks, refining category nomenclature and identifying subcategories that reflect recurring implementation patterns across the literature. For each building block, we adopt different classification scopes tailored to their specific technical characteristics, providing a finer-grained perspective on implementation approaches and challenges each category presents in data spaces.

4.1. Data interoperability

Data interoperability enables heterogeneous systems to exchange and interpret data while preserving semantic consistency across organizational boundaries [70]. As organizations increasingly participate in cross-domain data sharing, standardized approaches are required to address technical challenges spanning data models, exchange mechanisms, and data lifecycle tracking systems. We organize these interoperability requirements into three categories:

- **Data models**: Semantic frameworks for common data understanding and interpretation.
- **Data exchange**: Protocols, interfaces, and intermediary systems for data access and transfer.
- **Provenance and traceability**: Mechanisms documenting data lineage and transformations for transparency and verification of data quality through verifiable audit trails.

4.1.1. Data models

They provide formal representations of data elements and their relationships to ensure both semantic and syntactic data coherence across systems. The implementation of data models in data spaces must address the integration of heterogeneous data sources with diverse formats and semantics while preserving consistency during data exchange operations. Our analysis of the literature reveals three distinct categories, as shown in Table 3: (1) targeted vocabularies for specific sectors, (2) AAS solutions for industrial asset representation, and (3) methods and tools for ontology development and alignment.

Sector-specific data models establish standardized vocabularies and structures for sector-specific data representation. In energy [71] and manufacturing [76], CIM provides taxonomies for power utility network modeling, supporting applications like load forecasting and electricity balancing. Manufacturing implementations utilize SysML for mechatronic product representation [74] and AutomationML for modeling factory capabilities in the Smart Factory Web [72,73]. Moreover, SysML is extended to model entire data spaces [75], enabling cross-sector collaboration in data space architecture design.

FIWARE Smart Data Models,[10] built on the ETSI NGSI-LD specifications [100], provide open and standardized data structures for semantic interoperability across domains [77,80,81]. In mobility, they are used to model urban Digital Twin (DT) data related to buildings, public transportation, and traffic monitoring [79], whereas standards such as DATEX-II model traffic flows and GTFS transit data [78]. Cultural heritage applications models extend CIDOC CRM (ISO 21127:2014) and the Europeana Data Model (EDM) in the Heritage Digital Twin (HDT) ontology [82], while INSPIRE data models address geospatial data requirements [83].

Asset Administration Shell (AAS), initially proposed by the German platform Industrie 4.0 and now standardized through the IDTA,[11] provides data models for encapsulating asset information, incorporating both static specifications and dynamic operational data to enable structured data exchange throughout the asset lifecycle. The use of AAS submodels for data modeling in data spaces spans multiple industrial purposes, from manufacturing asset and process representation [73,85, 87–91] to its use as an enabler for resilience assessment in factory reconfiguration [86], offering information such as the probability of failure. Particularly significant is the DTS-RM [84], which adopts AAS as the core data model for DT representation in data spaces.

FA^{3}ST software ecosystem simplifies creation and deployment of AAS-compliant DTs [92], demonstrated in carbon footprint modeling for DPPs [93] and manufacturing applications [94].

Methods and tools for achieving semantic interoperability in data spaces range from specialized semantic modeling frameworks to automated vocabulary mapping solutions. PLASMA [95] facilitates semantic model creation through visual interfaces that assist participants in creating and refining semantic models [64], complemented by ATLAS's [96] capabilities for generating multi-format data model specification. Advanced implementations incorporate ML for automated vocabulary alignment between local and data space vocabularies [97–99].

[10] https://www.fiware.org/smart-data-models/.

Table 3
Classification of approaches for data models in data spaces.

Category	Definition	Primary studies
Sector-specific	Data models defining vocabularies and structures for sector-specific data.	Energy [71], Manufacturing [72–77], Mobility [78–81], Cultural Heritage [82,83]
Asset Administration Shell (AAS)	Data models for the digital representation of industrial assets.	AAS Submodels [73,84–91], FA^{3}ST Service[a] [92–94]
Methods and tools	Semantic model creation, vocabulary alignment, and AI-assisted data modeling.	PLASMA[b] [95], ATLAS[c] [96], AI-Assisted Methods [97–99]

[a] https://github.com/FraunhoferIOSB/FAAAST-Service.
[b] https://github.com/tmdt-buw/plasma.
[c] https://mff-uk.github.io/atlas-docs/.

Table 4
Classification of approaches for data exchange in data spaces.

Category	Definition	Primary studies
Exchange protocols	Standards that define rules and methods for transmitting data between systems.	HTTP/HTTPS [34,72,90,101–104], MQTT [72,81,88,101,105–109], AMQP [108]
Application Programming Interfaces (APIs)	Interfaces that specify how systems can interact with a service or application.	Generic REST APIs [110–113], OGC SensorThings API[a] [73,101,105,114], NGSI-LD Context Broker [9,77,80,102,103,115,116]
Intermediary systems	Middleware tools to facilitate data exchange, transformation or streaming between systems.	Apache Camel[b] [34,35,72,106], Apache Flink [117], Apache Kafka[c] [103,108,118–120], Apache Pulsar[d] [108], Liqo[e] [121], OPC UA IoT Agent[f] [102]

[a] https://github.com/opengeospatial/sensorthings.
[b] https://github.com/apache/camel.
[c] https://github.com/apache/kafka.
[d] https://github.com/apache/pulsar.
[e] https://github.com/liqotech/liqo.
[f] https://github.com/Engineering-Research-and-Development/iotagent-opcua.

4.1.2. Data exchange

It encompasses the actual exchange of data assets between participants, relying on semantic interoperability established through shared data models. In data spaces, it requires enabling interoperable flows across systems via standardized protocols and interfaces.

Our analysis of primary studies identifies three interconnected categories, as shown in Table 4: (1) data exchange protocols establishing standardized methods for data transmission and network encapsulation, (2) API defining interaction patterns between systems and services, and (3) intermediary systems providing middleware infrastructure.

Exchange protocols are used for the actual data transfer once a data-sharing agreement is established. Our analysis reveals that data spaces mainly rely on conventional transfer protocols, with HTTP [90,

[11] https://industrialdigitaltwin.org.

101,104] and HTTPS [34,72,102,103] serving as the foundation for RESTful interfaces. For real-time and event-driven data exchange, MQTT emerges as a widely adopted protocol in IoT scenarios [81,88, 106], demonstrating suitability for continuous data streams from multiple sources [105,108]. Studies show its capability for real-time data injection and message buffering [109], implemented through brokers like Eclipse Mosquitto[12] [107] and Moquette[13] [72]. Some implementations combine multiple protocols, utilizing MQTT for sensor data collection while maintaining HTTP endpoints for data queries [101]. For advanced message handling, [108] proposes the AMQP as an alternative, offering features such as message queuing and routing capabilities.

Application Programming Interfaces (APIs) define standardized methods governing system interactions and data exchange operations. They abstract underlying implementation details to provide interoperable access to resources and services. In data spaces, several REST-based API approaches have been implemented, with two predominant standards emerging across the literature, though other generic REST APIs are also utilized in some studies [110–113]:

- **OGC SensorThings API** provides a standardized specification for IoT data management, offering unified data access and observation handling, primarily implemented through the FROST server [73,101]. Studies explore its implementation in both synchronous and asynchronous communication patterns [105], demonstrating its versatility in various architectures. [114] exemplifies its practical application within cloud-based microservices for mobility data processing.
- **NGSI-LD Context Broker** implements the NGSI-LD API for context management, enabling standardized data storage and querying while maintaining information in an interoperable format [9, 80,115]. Although various implementations exist, the FIWARE Orion Context Broker[14] is the most widely adopted and referenced solution in the literature. Its versatility is demonstrated across domains, from manufacturing applications facilitating industrial data exchange [77,102] and platform integration [116], to real-time smart energy systems [103].

Intermediary systems serve as middleware that facilitate interoperability between systems through data translation and routing. Apache Camel and Apache Flink emerge as key solutions in connector implementations: in the DSC for handling data routing and message transformation [34,106], and in the Trusted Connector for policy enforcement [35,117].

Message-oriented middleware solutions incorporate Apache Kafka [119,120] and Apache Pulsar [108], with Kafka supporting data ingestion pipelines [118] and historical data management [103]. For infrastructure-level integration, the Liqo Gateway [121] implements virtual tunnels for secure inter-cluster communication, addressing orchestration needs beyond traditional data exchange mechanisms. Specific adapters like OPC UA IoT Agents [102] bridge industrial systems by translating between OPC UA and NGSI protocols.

4.1.3. Provenance and traceability

Provenance refers to tracking data origin and ownership, while traceability monitors the data lifecycle and usage across systems. Together, they support trust, accountability, and transparency in data spaces. Our analysis identifies two main technological approaches (see Table 5): (1) semantic methods using ontologies for provenance representation, and (2) DLT-based solutions offering verifiable records of data operations.

Table 5
Classification of approaches for provenance and traceability in data spaces.

Category	Definition	Primary studies
Semantic provenance	Ontology-based provenance modeling.	W3C PROV[1] [71,118,122], Custom Ontologies [123]
Distributed Ledger Technology (DLT)	DLT-based solutions for data traceability and integrity.	Data Storage [115,124–126], Provenance [127], Accountability [128–130], Architecture Components [131–133]

Semantic provenance approaches employ standardized frameworks to create machine-readable representations of data origin and lineage. For this purpose, the W3C PROV[15] ontology can be integrated into the W3C DCAT metadata standard. This integration allows structured provenance representation across data ecosystems [71, 118,122]. To further address analytic provenance challenges, authors in [123] propose an architecture based on custom ontologies and translator components that harmonize provenance information from diverse sources.

Distributed Ledger Technologies (DLTs) provide verifiable traceability through immutable transaction records. While various DLT types exist, blockchain emerges as the predominant technology used in data spaces. Authors in [127] propose a SDL framework combining blockchain and smart contracts for decentralized provenance verification. For immutable data storage, [115] implements blockchain-based storage for manufacturing sensor data integration, while [124] utilizes it for health records traceability in global health data spaces. In manufacturing, [125] implements dedicated blockchain infrastructure within the MANU-SQUARE platform to maintain immutable records of IoT sustainability assessment data. Moreover, [126] proposes the use of DLT for sharing reports on coordination performance in critical infrastructure networks, enabling secure information exchange on cyber threats within smart power grids.

In terms of accountability mechanisms, while blockchain facilitates transparent tracking of data access and usage in food supply chains [129], authors in [128] leverage the Ocean Protocol[16] with NFT to manage copyright ownership and tokenized data access rights. Moreover, the Trans-Border Trusted Data Space (TTDS) framework implements smart contracts over DLTs to address traceability [130]. In a more general context, [131] outlines the integration of blockchain for implementing IDS RAM components, with [132] specifically implementing the Clearing House, Metadata Broker, and Identity Provider using the IOTA[17] DAG-based DLT. Similarly, [133] proposes a decentralized data space architecture for drone data sharing in 6G networks, where blockchain serves as a core enabler.

4.2. Data sovereignty

Data sovereignty ensures that participants in a data space maintain control over their shared information while verifying its authenticity and reliability. As data-sharing ecosystems expand, robust approaches are needed to address identity, trust, and usage control enforcement. Following the DSSC Blueprint [22], we organize these requirements into three categories:

- **Identity management**: Identity frameworks for authentication and authorization of data space entities, including participants, components, and service interactions.
- **Trust framework**: Mechanisms establishing trust through verifiable attestations.
- **Usage control**: Specification and technical enforcement of data access and usage policies.

[12] https://github.com/eclipse-mosquitto/mosquitto.
[13] https://github.com/moquette-io/moquette.
[14] https://github.com/telefonicaid/fiware-orion.
[15] https://www.w3.org/TR/prov-overview/.
[16] https://oceanprotocol.com/.
[17] https://www.iota.org/.

Table 6
Classification of approaches for identity management in data spaces.

Category	Definition	Primary studies
Centralized	Approaches that rely on central authority or hierarchy.	PKI[a] [35,134], OAuth[b] [34,102,117,135], FIWARE Keyrock[c] [9,77,107]
Decentralized	Solutions based on distributed identity standards.	DIDs[d] , VCs, VPs[e] [128,131,132,134,136–140]

[a] https://www.ietf.org/rfc/rfc2459.txt.
[b] https://datatracker.ietf.org/doc/html/rfc6749.
[c] https://keyrock-fiware.github.io/.
[d] https://www.w3.org/TR/did-1.0/.
[e] https://www.w3.org/TR/vc-data-model-2.0/.

4.2.1. Identity management

It ensures that participants can authenticate, verify claims, and control access in data spaces. We identified two architectural approaches being used in primary studies, as shown in Table 6: (1) centralized solutions relying on single authority, and (2) decentralized infrastructures leveraging standards for SSI.

Centralized solutions offer unified management of participant identities and authentication processes through a central authority. Aligned with the IDS RAM, early implementations adopted PKI-based infrastructures relying on X.509 certificate hierarchies for service and connector authentication and provisioning [35,134]. Alternatively, some approaches leveraged FIWARE Keyrock as an IAM system [9,107], integrating it with OAuth-based authorization to issue token-based credentials for securing connector interactions [77,102,117,135]. Building on these methods, [34] combined OAuth with X.509 certificates within the DSC to ensure token integrity.

Decentralized solutions distribute the responsibility for managing participant identities across multiple independent entities or nodes with no central authority. Recent data space initiatives align with decentralized identity frameworks based on W3C DID [128,131,132,137], extending their functionality to support VC and VP [139].

Beyond identity authentication, VCs are leveraged to issue cryptographically verifiable claims. While [136] proposes digital wallets for VCs, [134] introduces an on-behalf-of delegation model for entities to delegate data access and control rights to trusted agents. Recent implementations combine data space membership VCs within OIDC login endpoints for federated identity, as demonstrated in [110]. In [137], authors leverage ZKP-based VCs selective disclosure using the BBS+[18] scheme to verify participants' sensitive information without full disclosure, preserving privacy and offering fine-grained control over how data is exposed and processed [138,140].

4.2.2. Trust framework

It ensures that: (1) participants adhere to established technical specifications and governance procedures [70], and (2) participants can exchange data without compromising security or privacy. We elaborate on this and derived the following subcategories for the selected studies, as summarized in Table 7: (1) conformity assessment approaches that ensure data space participants comply with predefined technical and governance standards, (2) attestation verification mechanisms that validate identity and security claims, and (3) privacy and security mechanisms.

Conformity assessment involves evaluating whether a participant, product, system, or service aligns with established standards and regulatory requirements. It focuses on long-term adherence to regulatory frameworks or technical standards. Authors in [142] introduced the CARiSMA tool for assessing data consumer adherence to provider-defined privacy preferences and GDPR Article 5, later expanding this work with an ontology for machine-readable GDPR constraints in data sharing agreements [143]. Similarly, the work in [144] evaluates FL frameworks against GDPR-aligned criteria for the EHDS. In parallel, [145] proposes a credential-based whitelisting mechanism for automated trustee selection, implemented as an EDC extension.

Attestation verification ensures that the information provided by a participant can be trusted by validating specific claims at a given point in time (rather than long-term conformity assessment). Leveraging VCs beyond *just* identity management (refer to Section 4.2.1 for more details), authors in [136] present the Data Exchange Agreement (DEXA) protocol, which encapsulates data agreements within VCs and VPs. When a participant needs to prove compliance with a data agreement at a given point, a VP can be created, selectively presenting relevant parts of the agreement for attestation verification [110,139]. Similarly, [148] leverages smart contracts to create verifiable attestations for data-sharing agreements, using Ethereum-based DIDs and DLTs to establish trust between law enforcement and research entities. This approach aligns well with cross-border identity verification requirements analyzed in [147]. Herein, authors analyze EU national healthcare infrastructures' readiness for cross-border electronic identification under the eIDAS. Building on this, [134] combines eIDAS-based identity authentication with VC-based attestation verification, enhancing the reliability and security of cross-border identity verification processes.

Privacy and security enable trust through embedded privacy, security, and compliance guarantees in data spaces. Herein, PET encompasses a range of cryptographic and data protection techniques that mitigate privacy risks while enabling secure data processing, sharing, and analysis without exposing sensitive information. The application of PETs in data spaces has grown alongside the increasing demand for mechanisms that ensure data sovereignty during usage [156]. We identified several PET applications in data spaces. For instance, anonymization techniques are employed to protect sensitive data and prepare it for secure sharing [149,150]. Authors in [151] develop privacy-preserving ML methods using SMPC and FL, while [152,153] employ HE to enable computations on encrypted data. ZKPs are proposed to be used for verification without revealing sensitive information [137,138]. Likewise, [135] applied SMPC in pulp and paper manufacturing to enable confidential life cycle assessments.

Advanced encryption is also explored, with studies implementing ABE in data spaces [138], including [154] combining ABE and TEE within IDS-based architectures. For security evaluation, [155] applies the STRIDE framework to identify vulnerabilities across trust boundaries in IDS, addressing emerging threats and proposing mitigation solutions.

4.2.3. Usage control

It encompasses and extends traditional access control, regulating not only initial access to data but also how data and resources are used after access is granted. While access control determines whether a user can access data, usage control further governs how that data can

Table 7
Classification of approaches for trust framework in data spaces.

Category	Definition	Primary studies
Conformity assessment	Verification of compliance with legal, regulatory or contractual requirements.	Legal Compliance (GDPR [141]) [142–144], Whitelisting Mechanisms [145]
Attestation verification	Validation of claims and credentials through standardized methods.	Regulatory Frameworks (eIDAS [146]) [134,147], Contractual Agreements [110,136,139,148]
Privacy and security	Technologies and methods for data protection and privacy preservation.	Anonymization [149,150], SMPC [135,151], HE [152,153], ZKP [137,138], TEE [154], Encryption [138,154], Threat Modeling [155]

[18] https://github.com/decentralized-identity/bbs-signature.

Table 8
Classification of approaches for usage control in data spaces.

Category	Definition	Primary studies
Policy specification	Defining rules and conditions for data access and usage.	Access Control [112,118], Terms [157], ODRL[a] [72,117,136], DSL [35,158], Quality Assessment [159], Editors [11,160,161]
Policy negotiation	Contract agreement negotiation between providers and consumers.	Counter Offers [132,143,157], Connector-Based [125], Policy Reasoning [139], Dynamic Pricing [162]
Policy transformation	Converting specified policies into machine-readable formats.	PTP [117], Policy Languages: D° [163], LUCON [35], MYDATA[b] [160]
Policy enforcement	Ensuring continuous compliance with policies during data usage.	ODRL [164,165], Generic Solutions [35,76,130,131,157], XACML[c] [9,35,72,77,102,117,138,166]

[a] https://www.w3.org/ns/odrl/2/.
[b] https://developer.mydata-control.de/.
[c] https://www.oasis-open.org/standard/xacmlv3-0/.

be processed, shared, stored, or modified over time, creating continuous protection throughout the data lifecycle. This approach enables data owners to maintain sovereignty over their data through machine-readable policy specification and enforcement. We categorize selected studies along the four stages of policy lifecycle [3], as shown in Table 8: (1) policy specification, where rules and conditions for data access and usage are defined, (2) policy negotiation for agreement establishment between parties, (3) policy transformation into machine-enforceable formats, and (4) policy enforcement ensuring compliance during data usage.

Policy specification refers to the formal definition of rules and conditions that govern how data is accessed, shared, processed, and used within the data space. This includes access control schemes, with implementations ranging from RBAC [112] to more flexible ABAC [118]. Authors in [157] provide a list of data-sharing terms (e.g., pricing model, quality) that can be specified through formalized policy expressions. While [35] proposes the use of DSL for policy specification, [158] introduces DSPOL, a high-level policy language with built-in verification and validation capabilities to detect inconsistencies.

Nevertheless, the W3C ODRL ontology remains the predominant solution in reference implementations [72,117], with [136] encapsulating ODRL policies into VCs. Supporting policy management, [159] introduces the Context-Aware Policy Analysis (CAPA) framework for quality assessment, while [11,160] present visual editor tools to graphically assist participants on policy specification. Furthermore, recent work in [161] demonstrates LLMs capability to generate ODRL-based usage policies.

Policy negotiation refers to the process through which participants agree on the terms, conditions, and rules for data sharing and usage. Authors in [157] suggest a conceptual framework enabling iterative negotiation through counter-offers until mutual agreement is reached, with [132] defining a workflow for implementing this mechanism in DSP-based data spaces. In addition, [143] defines the structure of digitally signed and GDPR-compliant counter-offers in healthcare domains. Similarly, [125] conceptualizes a connector-based negotiation process within the MANU-SQUARE platform, where connectors must reach policy agreement before data exchange, with agreed policies then deployed within connectors.

For automating policy compatibility verification, [139] presents the Gaia-X Policy Reasoning Engine[19] that transforms ODRL policies into RDF triples and uses SPARQL queries to determine if provider policies and consumer usage intentions can reach agreement. To optimize data pricing, [162] models policy negotiation as a combinatorial auction problem, implementing a VCG-based mechanism [167] to determine transaction prices.

Policy transformation refers to the process of adapting or converting policies from one format, framework, or standard to another, ensuring they remain applicable and enforceable. Once a data-sharing agreement has been reached, usage control requires the translation of high-level policy specifications, specified in ODRL, into machine-readable formats, which are technology-dependent. In [117], authors propose a PTP to convert ODRL policies into CEP programs. In [163], authors implement a transformation tool for D° language, which is a DSL that includes an extension for dynamic IDS identifier mapping. Authors in [160] present a policy editor and transformation tool for MYDATA, while [35] presents a transformation tool for LUCON policy language used in the Trusted Connector.

Policy enforcement refers to the process of ensuring that the defined policies are actively applied and followed by all participants. After data-sharing policies are agreed upon and converted into a machine-readable format, policy enforcement must ensure adherence to agreements and prevent unauthorized access and usage of data. Primary studies differ on how enforcement is designed and implemented.

While ODRL is used to specify policies, it cannot be directly used for enforcement. We found two studies that propose extending ODRL so that it can also be used for enforcement without the need to transform it to other enforceable languages. The work in [165] proposes a minor extension to enforce dynamic time-dependent constraints, while [164] extends the ODRL ontology with enforcing features.

On the other hand, we found several studies relying on XACML standard, which is an enforceable language used to define access control rules that proposes architectural components to implement enforcement of XACML-defined policies, including the PAP for policy management, PDP for evaluation, and PEP for execution.

Across data spaces, we found that FIWARE initially implemented XACML components through AuthzForce[20] and Wilma[21] [9,77,102], later extended in [117] with additional access and usage PDPs implemented via KeyRock and Apache Flink. XACML architectural patterns are also leveraged in other solutions, including the LUCON [35,166] and MYDATA [72] usage control tools.

Alternative approaches include the use of sticky policies [168], where policies remain persistently attached to data. In this context, [138] proposes using ABE to attach control policies directly to encrypted data, integrating with XACML-based policy enforcement. While not based on XACML, the PLATOON[22] usage control tool implements policy enforcement within the DSC, offering an alternative approach as demonstrated in [76]. We also found primary studies using custom approaches, with [157] proposing a conceptual microservice-based architecture, [35] leveraging message routing frameworks like Apache Camel, and works in [130,131] suggesting smart contracts for automated usage enforcement.

4.3. Data value creation enablers

Data value creation enablers provide mechanisms for describing, discovering, and utilizing data resources. These capabilities ensure that participants can effectively locate data assets and subsequently derive value from them. We categorize selected studies according to these three categories [22]:

- **Data offering**: Standardized metadata descriptions of offered data assets and services.

[19] https://gitlab.com/gaia-x/lab/policy-reasoning.

[20] https://github.com/authzforce/restful-pdp.
[21] https://fiware-pep-proxy.readthedocs.io/en/latest/.
[22] https://github.com/PLATOONProject/PLATOON_DATA_USAGE.

Table 9
Classification of approaches for data offering in data spaces.

Category	Definition	Primary studies
Ontology-based	Ontologies and linked data principles for structuring metadata.	IDS Information Model [2] (RDF[a], OWL[b]): [34,76,118,169–172], Knowledge Graphs [71,173,174], AI-Enhanced Metadata [97–99,161,175]
Credential-based	VCs for self-descriptive metadata.	Gaia-X Self-Descriptions [19]: [86,176]

[a] https://www.w3.org/TR/rdf12-concepts/.
[b] https://www.w3.org/TR/owl2-overview/.

- **Publication and discovery**: Mechanisms for registering, indexing, querying, and retrieving data assets.
- **Value creation services**: Applications, tools, and frameworks for data processing and analytics, supporting the integration of data spaces with external platforms.

4.3.1. *Data offering*

It encompasses metadata descriptions of data assets and services, outlining distribution methods, formats, access, and usage conditions. Implementation approaches converge around the W3C DCAT[23] vocabulary as a common standard for machine-readable asset descriptions.

To structure metadata in data spaces, we identified two primary approaches in the literature, as shown in Table 9: (1) ontology-based models leveraging semantic web technologies such as the RDF, OWL and DCAT for structured metadata representation, and (2) credential-based descriptions employing VCs to encapsulate metadata in a self-descriptive and cryptographically verifiable format. Notably, these approaches are complementary rather than mutually exclusive, as credential-based descriptions frequently incorporate ontological structures to express claims [19].

Ontology-based approaches implement semantic frameworks like the IDS Information Model, formally introduced by [170], which utilizes RDF for structured metadata representation and OWL for expressing asset relationships. Several studies validate and extend its applicability across domains. Authors in [169] apply the model for ontology-driven metadata representation in industrial contexts, while the work in [34] integrates it into the DSC for dynamic metadata alignment and automated catalog management. Further leveraging RDF, the model is applied to describe connector metadata [171] and generate RDF triples for mobility asset descriptions [118]. In [172], authors present the DS4MR ontology for metadata representation within manufacturing data spaces, while [76] develops the CORDS ML ontology, based on the ML Schema (MLS)[24] ontology, to describe ML models in data spaces.

To improve semantic integration and metadata linking, unified knowledge graphs are applied for integrating distributed metadata in energy domains [71], while this approach is also extended to battery production processes in [173]. An ontology for multimodal knowledge graphs that merges visual, sensor, and location data in smart cities is proposed in [174], reusing established ontologies such as GeoSPARQL.[25]

Complementary, emerging approaches leverage AI for enhancing metadata quality [97]. Several studies [98,99,161,175] extend this approach through prompt engineering with LLMs to facilitate metadata generation and enrichment, collectively reducing manual data preparation efforts.

[23] https://www.w3.org/TR/vocab-dcat-3/.
[24] https://github.com/ML-Schema/core.
[25] http://schemas.opengis.net/geosparql/1.0/geosparql_vocab_all.rdf.

Credential-based approaches implement Gaia-X Self-Descriptions that encapsulate structured metadata within VCs, establishing cryptographic verification mechanisms that enhance trust in federated data ecosystems. While ensuring authenticity and identity binding, these descriptions can still incorporate RDF vocabularies or OWL ontologies through JSON-LD structures. Implementation examples include its use within the FLEX4RES framework for manufacturing resilience assessment [86] and the PHT framework for healthcare asset descriptions [176].

4.3.2. *Publication and discovery*

Publication ensures proper metadata release with schema validation and integration into repositories, while discovery enables retrieval through metadata searches, semantic queries, and catalog access. Table 10 presents our categorization of approaches identified in the literature, distinguishing between: (1) publication technologies for metadata validation and registration, and (2) discovery mechanisms for metadata-driven search across catalogs.

Publication encompasses different metadata management processes, including storage and validation to facilitate its accessibility in data spaces. RDF triple stores provide persistent storage [71,171], while W3C SHACL enforces schema compliance before publication, as demonstrated in [71] using Trav-SHACL validation [181]. Alignment with FAIR principles varies across studies: CkanFAIR[26] assessment tool [177] evaluates dataset compliance before publication, structured metadata encapsulation [176] improves discoverability, and FAIR Digital Objects [178] create a common abstraction layer for cross-domain data spaces.

Discovery mechanisms facilitate the location and query of data offerings across catalogs. We identified W3C SPARQL as the predominant standard in literature for implementing semantic queries in data spaces, specifically for RDF triple stores established during metadata publication [71,72,104,127,171]. SPARQL-based asset search with JSON-formatted results visualization for industrial assets is demonstrated in [73], while SPARQL endpoints alongside GraphQL for dynamic discovery in research data spaces are implemented in [179]. REST-to-SPARQL translation in a metadata broker for manufacturing data spaces is leveraged in [172].

Complementary approaches include tabular search techniques [180], the FIWARE-based IDS broker [102] that integrates NGSI registries with a CKAN[27]-powered data catalog portal, and emerging AI-enhanced models [98,99] for query optimization and semantic discovery.

[26] https://github.com/datalab-unisalento/CkanFAIR-tool/.
[27] https://github.com/ckan/ckan.

Table 10
Classification of approaches for publication and discovery in data spaces.

Category	Definition	Primary studies
Publication	Structured metadata storage, validation, publication and release.	RDF Triple Stores [71,171], SHACL[a] [71], FAIR Principles [176–178]
Discovery	Metadata querying and retrieval via federated search and registries.	SPARQL[b] [71–73,104,127,171,172,179], Tabular Search [180], NGSI Registries [102], AI-Enhanced [98,99]

[a] https://www.w3.org/TR/shacl/.
[b] https://www.w3.org/TR/sparql11-query/.

Table 11
Classification of approaches for value creation services in data spaces.

Category	Definition	Primary studies
Data tools	Tools and services for data visualization, transformation, enrichment and analytics.	Visualization [95,112,182,183], Data Apps [80,92,97,98,116,161,184], AI Analytics [77,114,118,133,185,186]
Platform integration	Mechanisms connecting data spaces with external technologies and computing infrastructures.	DTs [79,84–94,187], Marketplaces [72,73,125,188]
Use case development	Data space implementations and specific use cases.	Refer to Table 12

4.3.3. Value creation services

They enhance data spaces by transforming raw data into actionable insights through processing, integration, and sector-specific functionalities. This category directly interacts with business building blocks by supporting sector-driven use cases and functional requirements, ensuring that data services align with economic models and operational needs. We structure the literature into three key categories, as shown in Table 11: (1) data processing services for visualization, transformation, and analytics, (2) platform integration connecting with external services and infrastructures, and (3) data spaces implementations and sector-specific use cases that define technical and functional requirements.

Data tools complement the essential capabilities of data spaces by acting directly upon datasets and adding value to data assets. We categorize the literature into three categories: (1) visualization interfaces for intuitive data interpretation, (2) data applications for processing and transformation, and (3) collaborative AI services for advanced analytics.

- **Visualization** tools serve as interfaces between users and data spaces, enabling data exploration and decision support. The PLASMA framework [95] facilitates semantic modeling through a visual interface that helps domain experts create models from complex data structures. For geospatial applications, interactive geo-dashboards for tourism data spaces that support strategic planning through spatial visualization are implemented in [182]. User experience with the GATEKEEPER platform's interface in healthcare contexts is evaluated in [112]. Interaction design patterns that balance security requirements with usability considerations, establishing guidelines for connector interfaces, are identified in [183].
- **Data applications** provide specialized functionality for transforming, processing, and analyzing data within data spaces. These applications can implement different data operations, including ML techniques for metadata extraction and quality assessment [97], and prompt-based LLM approaches for data exploration and cleaning [98,161]. IDS Data Apps for processing AAS-modeled DT data are implemented in [92], while the Blue Dataverse platform [184] includes IoT applications that process marine data for environmental monitoring. Specific data applications are deployed in [116] within the supplier infrastructure for sustainability metrics and analytics in manufacturing. Similarly, Snap4City, a modular environment for developing IoT and AI-driven applications in data spaces for data transformation and visualization, is introduced in [80].
- **AI analytics** complement data applications offering computational techniques within data spaces. MobiSpaces [118] exemplifies this approach with an Edge Analytics Suite featuring decentralized processing and resource allocation mechanisms that optimize AI task deployment, including an AI catalog of available ML tools, while similar orchestration of ML services in manufacturing is demonstrated in [77]. An AI-driven data pipeline for mobility data processing to model behavior patterns is outlined in [114], while an architecture based on ML applications instantiated within the DSC for collaborative traffic prediction is proposed in [185].
  Several studies demonstrate sector-specific approaches to AI integration in data spaces: FL is applied in EDC-based data spaces to enable policy-governed AI training in healthcare contexts [186], the CORDS framework facilitates secure ML model exchange in manufacturing data spaces [76], and collaborative model training across drone networks without sharing raw sensor data is achieved through FL in transportation applications [133].

Platform integration enables connectivity between data spaces and external systems, technologies, and computing infrastructures. We identified two predominant research areas: (1) DTs integration with data spaces, and (2) marketplace platforms that convert data spaces' abstract sharing capabilities into concrete business applications and value.

- **Digital Twins (DTs)** extend data spaces by providing digital representations of physical assets. The implementation of DTs as independent applications using data spaces primarily as sovereign data exchange mechanisms is discussed in [84,91,92,187]. This architectural separation is further developed in [93] with the EDC Extension for AAS[28] to reference external AAS services as data space assets [89], later used in the Manufacturing-X project [94]. Another integration approach using PLM adapters with Eclipse BaSyx[29] middleware to connect AAS with enterprise systems is depicted in [87,90].
  In contrast, a more integrated approach where DTs function directly as participants within the data space, offering and consuming data through connectors, is proposed in [79]. DSC-based sharing of AAS catalogs with orchestrators that query AAS registries to coordinate manufacturing assets is implemented in [85]. Similarly, data spaces as central repositories for AAS instances for the creation of DPPs in manufacturing are utilized in [88].
- **Marketplaces** implement interfaces that connect data spaces with users for discovering, accessing, and trading data assets [48,189]. Among the significant marketplaces identified, a MaaS marketplace integrating IDS connectors for supplier discovery and ranking based on sustainability metrics is implemented in [125]. The Smart Factory Web [72,73] extends this approach by leveraging IDS architecture to maintain sovereignty and usage control for sensitive industrial data when sharing factory capabilities across global production networks. Additionally, the ENERGATE project [188] creates an energy marketplace connecting stakeholders in the building sector to support retrofitting actions that reduce building energy consumption and operational costs.

Use case development captures studies addressing implementations and functional or technical requirements for sector-specific data spaces. This represents a significant portion of the literature. This category prioritizes research where data space implementation is the central contribution. Studies range from conceptual architectures [15,190,191] to working implementations [11,103] and proof-of-concepts [192]. Table 12 summarizes these approaches by sector of application.

[28] https://github.com/FraunhoferIOSB/EDC-Extension-for-AAS.
[29] https://eclipse.dev/basyx/.

Table 12
Classification of data space implementations and use cases addressed in the set of primary studies.

Sector	Primary studies
Agriculture	Agriculture Data Space [11,12,193–195], Food Supply Chains [129]
Cultural heritage	European Data Space for Cultural Heritage [191]
Energy	Italian Energy Data Space [196], Smart Grids [103,126], Renewable Energy [197]
Green deal	European Network for Earth System Modeling Data Space [198], Circular Economy [199,200]
Health	European Health Data Space (EHDS) [8,201], Thailand Health Data Space (THDS) [190], Healthcare Dashboard [192]
Manufacturing	Manufacturing Data Space [91,119,202,203], Logistics Data Space [204], IntraDataspace [113], Footwear Industry [205], Automotive [29]
Mobility	Seaport Data Space [9,110], +CityxChange [206], Urban Data Space [107,207,208], EdgeDS [10], Transportation [133,209], eMobility [111], Flanders Smart Data Space [104]
Public administration	Security [153,210], Dig. Certificates [140]
Research and innovation	Destination Earth [211]
Skills	SKILLAB [212]
Tourism	Balearic Islands Tourism Data Space [15]
Cross-Sector	DATA-EX [213], Telecom [120,214], International Testbed for Dataspace Technology (ITDT) [215], Trans-Border Trusted Data Spaces [130], Technical Architectures [216,217]

5. Analysis of the results

This section presents key findings from our SMS. Before addressing the RQs, we first contextualize the landscape by analyzing the publication venues, the geographical distribution of contributing authors, and the architectural approaches adopted across the studies. These elements provide important background for understanding how and where data space research is evolving and the frameworks shaping its development.

Publication venues: Fig. 5 illustrates the distribution of studies across publication venue types. Conference papers constitute the majority (59.7%), followed by journal articles (28.2%) and workshop papers (10.1%), with magazine articles representing the remaining 2%. This distribution reflects typical dissemination patterns in emerging technological domains, where conferences serve as the primary venue for introducing novel concepts. The significant presence of journal articles suggests maturation in certain aspects of data space research, while workshops indicate ongoing experimental work.

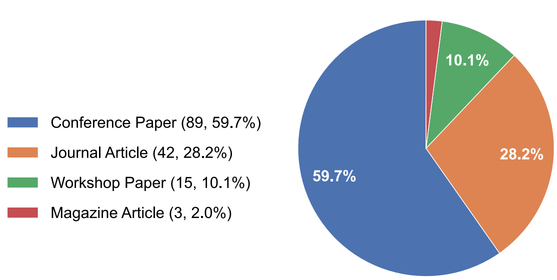

Fig. 5. Distribution of primary studies by publication type.

Regarding specific venues represented on Fig. 6, 53.7% of studies appeared in unique publication outlets, demonstrating the field's broad and multidisciplinary academic reach. The IEEE International Conference on Big Data represents the most significant concentration (7.4%), highlighting the natural alignment between data spaces and big data technologies. Dedicated forums for data space research include the ACM Web (WWW) conference (6%), which hosted the first International Workshop on SDS in 2023, and the eSAAM conference (5.4%), which focused on data spaces in its 2024 edition. Other prominent venues include the IEEE International Conference on Emerging Technologies and Factory Automation (ETFA) (4.7%), MDPI's Sensors and IEEE Access journals (2.7% each), and MDPI's Data and Applied Sciences journals (2% each). The remaining 13.4% of studies appeared in venues with exactly two publications each.

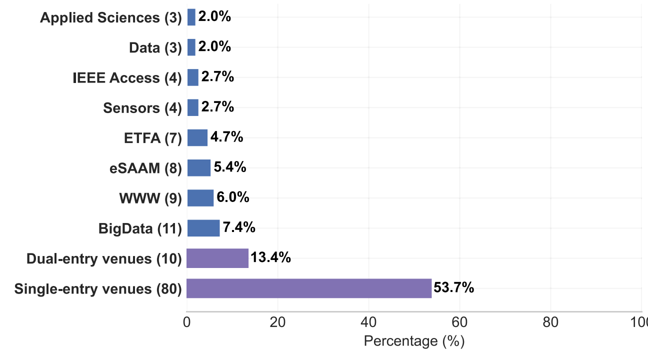

Fig. 6. Distribution of primary studies by publication venue.

The wide distribution of studies illustrates the interdisciplinary character of data spaces, but it also reveals a lack of dedicated publication venues, a gap that the International Workshop on SDS is beginning to address. While industry-led forums through IDSA, Gaia-X, FIWARE, and the European Data Spaces Symposium[30] serve as platforms for technical progress and ecosystem alignment, they remain primarily industry or policy-driven. This highlights the need for dedicated research-oriented forums to provide space for methodological innovation, critical analysis, and reproducible scientific contributions to the evolving data space landscape.

Geographical distribution: The distribution of author affiliations shown in Fig. 7 reveals European leadership in data space research (87.4%). Germany emerges as the dominant contributor (33.8%) of affiliations,[31] followed by Italy (10.8%) and Spain (9.6%). This reflects the strong influence of EU initiatives such as DSSC and Horizon Europe in shaping the research agenda and funding ecosystem around data spaces.

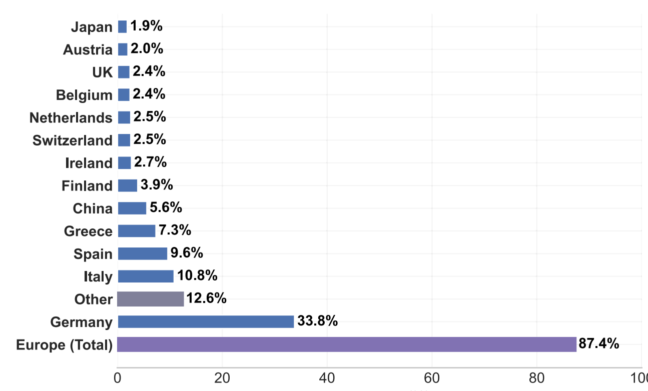

Fig. 7. Distribution of primary studies by geographic origin.

[30] https://www.data-spaces-symposium.eu/.
[31] Percentages reflect all author affiliations, counting multiple affiliations and recurring authors separately.

Germany's leading role aligns with its institutional involvement in foundational architectures and connector development, with Fraunhofer institutes initiating IDS and contributing significantly to connector implementations [33]. The presence of Italy and Spain among the top contributors further indicates European expansion beyond the initiating countries, likely facilitated by EU funding instruments that prioritize multi-country collaboration. While contributions from non-European regions remain limited, the presence of studies from China (5.6%), Japan (1.9%), and the United States (0.5%) suggests early signs of internationalization beyond the European policy framework that originally shaped data space development.

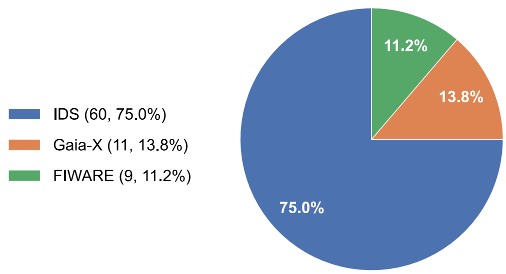

Fig. 8. Distribution of studies across reference architectures.

Architectural approaches: To further contextualize the technical landscape, Fig. 8 represents the distribution of reference architectures, while Fig. 9 shows the distribution of connector implementations. These figures represent explicitly mentioned architectures and connectors only, with 38.3% of the 149 primary studies (57 papers) specifically identifying their connector implementation. Studies that did not specify architectural frameworks are excluded from this analysis.

IDS dominates implementations (75%), followed by Gaia-X (13.8%) and FIWARE (11.2%). Similarly, IDS-based connectors predominate (35.1%),[32] with DSC (2020) emerging as the most common specific implementation (29.8%), followed by EDC connector (2021) (26.3%), Trusted Connector (2017) (5.3%) and TRUE Connector (2020) (3.5%). These findings are consistent with observations from [33], which describes the evolution of data space connectors from early monolithic designs toward more modular and extensible implementations as the EDC. Our study complements this perspective by quantifying adoption trends in academic research, confirming the central role of IDS and the growing prevalence of DSC and EDC as reference connector implementations.

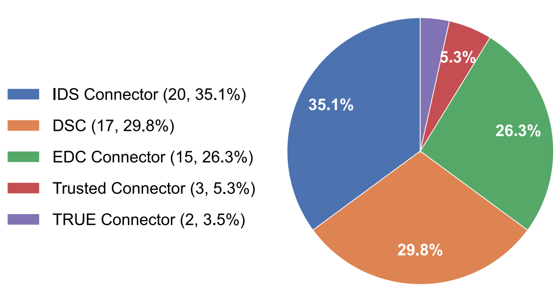

Fig. 9. Distribution of primary studies across connectors.

5.1. RQ1: What is the methodological maturity and technical novelty of data space research, and how has it evolved?

To address RQ1, we analyzed the primary studies using two complementary facets: *Facet 2 - Research Type*, which captures methodological maturity, and *Facet 3 - Technical Novelty*, which highlights the degree of innovation.

Maturity of the research: Considering *Facet 2- Research Type*, *solution proposal* (38.9%) is the most represented category, followed by *validation research* (25.5%) and *conceptual paper* (21.5%) (see Fig. 10, left-hand side pie-chart). This distribution, with nearly two-thirds of publications focused on implementation, indicates that data space research is primarily driven by technical realization rather than theoretical exploration. Looking at the temporal distribution of papers, Fig. 10 reveals a sharp increase in research activity from 2021 to 2024, peaking in 2024 with 47 studies. This surge aligns with the launch of the European Strategy for Data [5] (2020) and the emergence of operational reference implementations (e.g., Catena-X, Mobility Data Space) along with connector specifications (e.g., DSC, Trusted Connector, TRUE Connector, EDC) [33]. These technical foundations have enabled a shift from conceptual papers toward more solution-oriented and validation-focused research, providing researchers with established platforms to build upon and evaluate. This is evident in the growth of validation research, which increased from just 2 studies in 2021 to 13 in 2023. A similar trend is seen for *solution proposals*, while the number of *conceptual papers* has remained relatively stable since 2021.

In parallel, *experience papers* (7.4%), have started to emerge since 2022, documenting real-world implementation outcomes and challenges. *Opinion papers* (1.3%) reflect on practical deployments intended to guide future research. Despite this increased maturity, *evaluation research* remains notably limited (5.4%), exposing a critical gap in assessing the real-world effectiveness and impact of data space implementations.

Technical novelty: Considering *Facet 3 - Technical Novelty*, the trend toward practical realization is further reinforced by the distribution of technical novelty, as shown in Fig. 10 (right-hand side pie-chart). Most studies (48.3%) fall into the *reuse and integration* category, demonstrating the adaptation and integration of existing technologies, such as the IDS RAM, open-source connectors, and semantic vocabularies, into data space implementations. This is expected, as data spaces advocate leveraging existing technologies [2,18,70].

Meanwhile, 28.2% of studies present *novel approaches*, including novel architectures, protocols, or technologies. This indicates that, alongside adherence to established reference architectures, a significant portion of the community actively explores unresolved challenges where existing frameworks fall short. Rather than contradicting the reuse paradigm, these novel approaches often serve as precursors to future standardization and broader adoption. The remaining 23.5% of studies consist of non-technical contributions (e.g., opinion and experience papers), for which novelty is not applicable.

Insights: Analysis of methodological maturity and technical novelty reveals three key patterns in data space research:

- Data space research is **practice-driven with selective innovation**, focusing on implementation while maintaining targeted innovation in specific technical areas where existing frameworks fall short.
- The field demonstrates **methodological maturity progression with evaluation deficit**, progressing from concepts to implementations but lacking sufficient assessment of real-world effectiveness.
- Strategic **alignment with reference architectures enhances standardization** without limiting creativity, creating an ecosystem where reuse improves interoperability while supporting targeted extensions.

5.2. RQ2: What is the coverage, evolution, and interrelation of technical building blocks in data space research?

To address RQ2, we analyze how studies address *Facet 1 - Building Blocks*, focusing on the representation and evolution of core technical capabilities across the data space landscape.

[32] *IDS Connector* represents studies implementing IDS-based connectors without specifying the exact implementation variant.

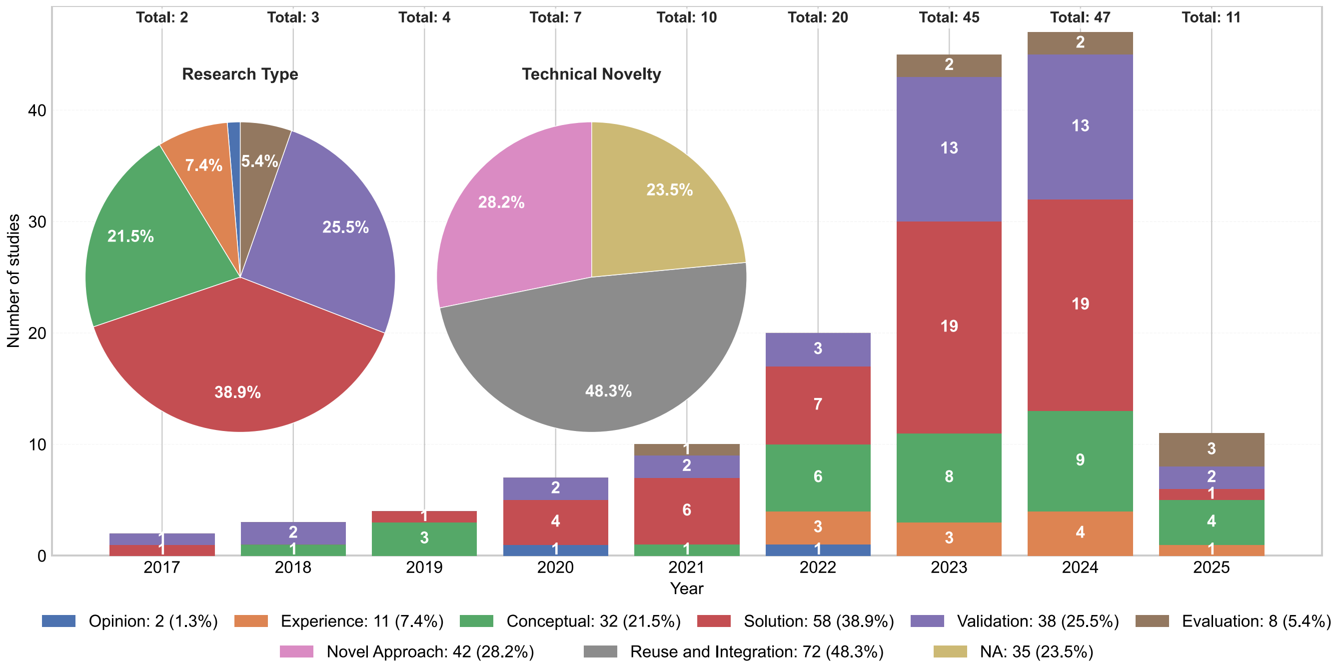

Fig. 10. Distribution of primary studies by research type and technical novelty over time.

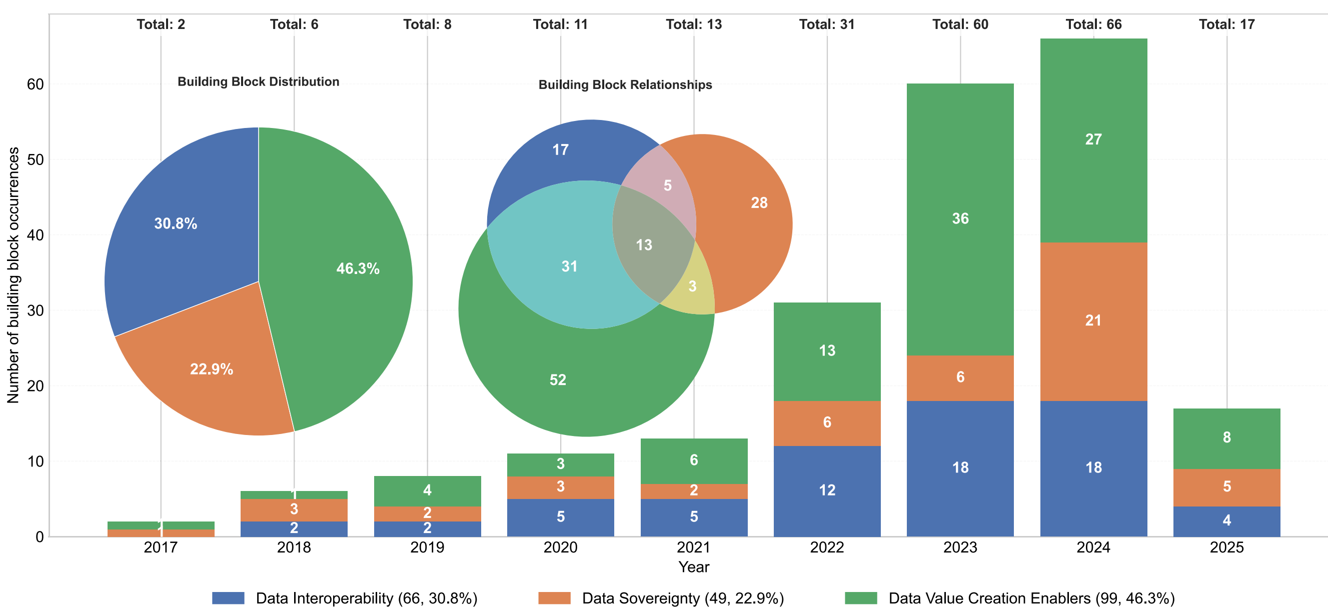

Fig. 11. Distribution of building block occurrences over time, and building block relationships.

Coverage of building blocks: Fig. 11 (left-hand side pie-chart) shows the distribution of building block occurrences across the primary studies. *Data Value Creation Enablers* are the most frequently addressed (46.3%), followed by *Data Interoperability* (30.8%) and *Data Sovereignty* (22.9%). This distribution reflects a strong research emphasis on enabling practical applications and value-generating services, while foundational and governance-related aspects receive comparatively less attention. Note that, as each study may address multiple building blocks, the total number of occurrences exceeds the number of primary studies.

Temporal evolution: All three building blocks have experienced steady growth from 2021 to 2024, with *Data Value Creation Enablers* showing the most pronounced increase (from 6 occurrences in 2021 to 36 in 2023). This trend mirrors the broader shift observed in Fig. 10, where research is moving from conceptual discussions toward solution-oriented and validation-focused contributions. The acceleration in value creation-related research suggests a potential imbalance. While researchers focus on extracting economic benefits from data spaces, the fundamental aspects of interoperability and sovereignty receive comparatively less attention, possibly reflecting market pressure for quick returns.

Relationships across building blocks: The analysis reveals (see Fig. 11 right-hand side Venn diagram) that only 13 studies address all three categories simultaneously, suggesting that most research efforts remain focused on isolated aspects of data space functionality. Notably, almost every study that addresses both *Data Sovereignty* and *Data Value Creation Enablers* also include *Data Interoperability* components, reinforcing the notion that interoperability serves as a technical foundation across the board. In contrast, *Data Sovereignty* often appears as a complementary feature rather than a core design element, suggesting a potential research gap in security and usage control mechanisms. This aligns with observations from [34], which observed that early implementations of data space solutions tend to prioritize data exchange over secure, policy-enforced control of the shared data.

On a closer look, Fig. 12 depicts the network of interlinkages between building block components, offering a finer-grained view of integration patterns. The strongest connections appear between *Data Value Creation Services* and both *Data Models* (22 links) and *Data Exchange* (19 links), indicating that value creation implementations heavily depend on both data modeling and exchange capabilities. *Identity Management* shows balanced integration with both *Usage Control* (10 links) and *Data Exchange* (8 links), underscoring its bridging role between sovereignty and interoperability requirements. In contrast, *Provenance and Traceability* shows relatively weak integration across the framework. Similarly, there is a minimal connection between *Data Sovereignty* components and *Data Value Creation* components, with most connections requiring *Identity Management* as an intermediary.

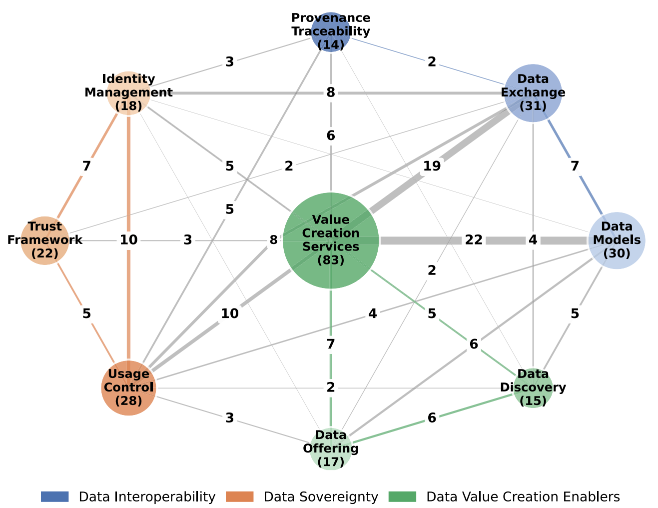

Fig. 12. Network visualization of co-occurrences between data spaces building block categories.

Overall, the network visualization reveals a siloed development pattern, where components within the same building block tend to be more tightly connected than those across other building blocks. This suggests that many current solutions focus on specific capabilities but lack holistic integration across interoperability, sovereignty, and value creation dimensions.

While this modularity might create misalignments, it aligns with the strategic direction of leading data space initiatives. Reference architectures (e.g., IDS RAM [2], DSSC [22]), along with reference implementations like SIMPL are contributing to create a modular ecosystem that could benefit from parallel development, rather than one single monolithic implementation. Hence, our findings confirm the deliberate architectural strategy being pursued by key initiatives.

Insights: Analysis of coverage, temporal evolution, and interrelation of technical building blocks reveals these patterns:

- **Value creation is driving the research agenda** as evidenced by its dominant representation (46.3%). Research increasingly prioritizes how data spaces generate economic and operational value, likely influenced by funding programs, real-world pilots, and market demands.
- **Sovereignty remains underexplored** despite its policy importance, appearing in only 22.9% of studies. This might be likely due to its technical complexity and limiting tooling for enforcing usage control.
- **Identity management plays a bridging role** in linking sovereignty and interoperability components, suggesting its potential as a key enabler of trust-aware data exchange.
- Data spaces building blocks **integration remains siloed rather than holistic**. Most research lacks a unified approach to interoperability, sovereignty, and value creation, presenting a clear opportunity for future work.

5.3. RQ3: What is the coverage, technical novelty, and interrelation of Data Interoperability in data space research?

To address RQ3, we elaborate on both *Facet 1 - Building Blocks* and *Facet 3 - Technical Novelty*, conducting a deeper analysis of *Data Interoperability* and its components: *Data Models*, *Data Exchange*, and *Provenance and Traceability*.

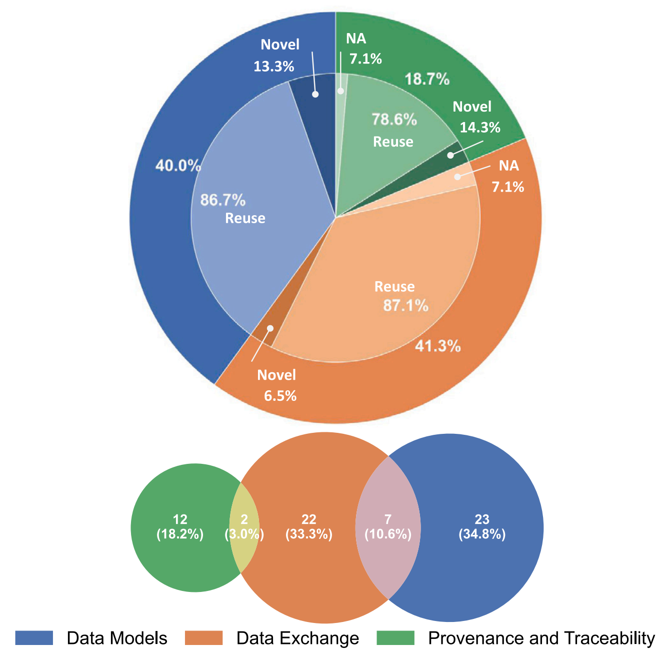

Fig. 13. *Data Interoperability* analysis: coverage and technical novelty (top), and component relationships (bottom).

Coverage: Fig. 13 (top, outer pie chart) shows the distribution of *Data Interoperability* components across primary studies. The coverage is relatively balanced between *Data Models* (40%) and *Data Exchange* (41.3%), while *Provenance and Traceability* (18.7%) is less represented. Compared to the IDSA Data Spaces Radar[33] (an industrial baseline), greater emphasis is placed on *Data Exchange* (58.9%), with lower focus on *Data Models* (24.7%), and similar attention for *Provenance and Traceability* (22.6%) (see Table 13 for detailed academic research vs. industrial implementation comparison).

Although academic research diverges from industry in its stronger focus on modeling, both domains reflect a common pattern: *Data exchange* is the most established aspect of interoperability, while provenance remains the least developed. Both domains show little focus on *Provenance and Traceability* (across both analyses). This indicates a persistent gap in data lineage mechanisms that might impact trust and compliance in operational data spaces.

[33] IDSA's repository of global data space initiatives (190 entries as of June 2024): https://www.dataspaces-radar.org/.

Table 13
Academic vs. industrial (IDSA Data Spaces Radar) focus comparison for *Data Interoperability* components.

Component	Academic	Industrial	Gap
Data models	40.0%	24.7%	Academic +15.3%
Data exchange	41.3%	58.9%	Industrial +17.6%
Prov. and traceability	18.7%	22.6%	Industrial +3.9%

Technical novelty: The three *Data Interoperability* components show distinct technical profiles and levels of innovation (see Fig. 13 top, inner pie chart). *Data Exchange* has the highest reuse rate (87.1%), reflecting widespread reliance on existing protocols (e.g., HTTPS, MQTT) and tools (e.g., NGSI-LD context brokers, OGC SensorThings API). Similarly, *Data Models* also exhibit high reuse (86.7%), mainly through AAS in industrial settings and FIWARE Smart Data Models predominantly in IoT and smart cities.

While aligned with the DSBA Technical Convergence Discussion Document [20] regarding FIWARE integration and IDSA guidance [6], the lack of user-friendly modeling tools remains a challenge, with research prototypes like PLASMA [95] and ATLAS [96] not yet operationalized.

In contrast, *Provenance and Traceability* shows higher novelty (14.3%) through DLT (mainly blockchain) solutions and semantic frameworks (e.g., W3C PROV), but contributions are often conceptual and lack detailed evaluations. Notably, few studies address alternative DLT types or non-DLT solutions, suggesting an opportunity for broader comparative research. Additionally, observability — monitoring operations for insights or anomaly detection — remains largely unexplored, even though the IDS RAM v5.0 [18] highlights it as a natural extension to provenance [70]. In sum, while reuse still dominates, these gaps present clear avenues for further research in provenance and semantic integration.

Relationships across components: The co-occurrence diagram (Fig. 13 bottom Venn diagram) shows moderate integration between *Data Models* and *Data Exchange* (7 studies). Notably, no study addresses *Data Models* and *Provenance and Traceability* together, nor does any comprehensively cover all three interoperability components. This suggests that research tends to specialize in specific interoperability aspects, with little emphasis on holistic, end-to-end solutions.

Insights: Analysis of coverage, technical novelty, and interrelation of *Data Interoperability* yields these findings:

- ***Reuse and Integration* dominates technical contributions**, reflecting industry convergence around mature technologies that favor compatibility over innovation.
- ***Provenance and Traceability* remains underdeveloped**, showing limited representation and minimal integration.
- No studies address all three interoperability components simultaneously, creating a **lack of holistic interoperability solutions** that integrate data modeling, exchange and provenance capabilities within unified frameworks.
- **Tooling and automation capabilities** are emerging but lack operational integration, with AI-assisted modeling and semantic alignment approaches remaining predominantly unexplored in operational settings.

5.4. RQ4: What is the coverage, technical novelty, and interrelation of Data Sovereignty in data space research?

To address RQ4, we build on *Facet 1 – Building Blocks* and *Facet 3 – Technical Novelty*, focusing on the three components of *Data Sovereignty* building block: *Identity Management*, *Trust Framework*, and *Usage Control*.

Coverage: Fig. 14 (top, outer pie-chart) presents the distribution of *Data Sovereignty* components across primary studies. *Usage Control* receives the highest attention (41.2%), followed by *Trust Framework* (32.4%) and *Identity Management* (26.5%). This differs from the IDSA Data Spaces Radar, where *Identity Management* dominates (29.5%), and both *Usage Control* (20%) and *Trust Framework* (12.6%) are less emphasized. These differences suggest that academic research prioritizes usage control mechanisms, while industry initiatives focus more on establishing identity infrastructure, as detailed in Table 14.

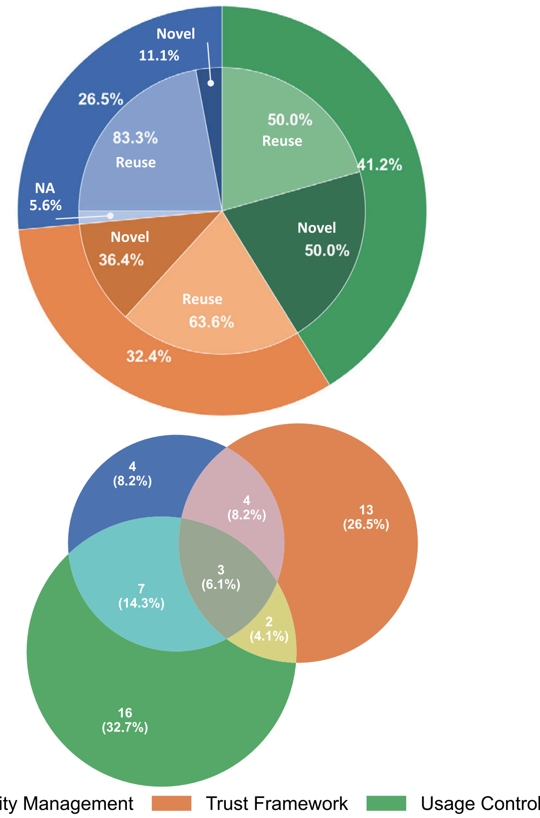

Fig. 14. *Data Sovereignty* analysis: coverage and technical novelty (top), and component relationships (bottom).

Technical novelty: The level of innovation varies across components (see Fig. 14 top, inner pie chart). *Identity Management* shows the highest reuse rate (83.3%), primarily relying on existing protocols like OAuth and OIDC, which are often integrated into connectors such as DSC and EDC.

In addition to widespread reliance on established standards, our analysis (see Table 6) reveals a shift from early data space implementations relying on centralized identity management to the more recent exploration of decentralized SSI frameworks. This evolution aligns with broader initiatives, including the Gaia-X Trust Framework [4] and the IDS RAM [2,18], which have progressed from centralized PKI toward decentralized models. Yet, fully decentralized solutions often require bridging partial trust relationships across data spaces. Consequently, federated identity approaches present an opportunity to preserve organizational autonomy while enabling cross-domain identity exchange without centralized control.

Table 14
Academic vs. industrial (IDSA Data Spaces Radar) focus comparison for *Data Sovereignty* components.

Component	Academic	Industrial	Gap
Identity management	26.5%	29.5%	Industrial +3.0%
Trust framework	32.4%	12.6%	Academic +19.8%
Usage control	41.2%	20.0%	Academic +21.2%

By contrast, *Usage Control* (50% novel) and *Trust Framework* (36.4% novel) exhibit greater innovation. Novel usage control mechanisms include runtime policy engines, DSL-based rules, and early-stage smart contract implementations for decentralized enforcement. However, few approaches evaluate their effectiveness, scalability, or conflict handling. Trust frameworks introduce concepts such as federated registries and negotiation protocols, but remain mostly conceptual or under-validated. Promising directions such as PETs and auditable smart contracts offer potential for dynamic, verifiable sovereignty enforcement but are not yet operationalized.

Relationships across components: Co-occurrence analysis reveals limited integration among *Data Sovereignty* components (see Fig. 14 bottom Venn diagram). The strongest relationship is between *Identity Management* and *Usage Control* (7 studies), while *Trust Framework* remains slightly disconnected. This fragmentation suggests a lack of governance strategies and enforcement mechanisms across the literature.

Insights: Analysis of coverage, technical novelty, and interrelation of *Data Sovereignty* reveals these patterns:

- Academic research differs from industry by emphasizing **usage control mechanisms over identity services** as the primary means of enforcing data sovereignty, focusing on policy-based governance rather than authentication alone.
- *Data Sovereignty* research remains **methodologically fragmented**, with minimal integration across components, indicating the need for more unified governance frameworks in data spaces literature.
- While innovative approaches in trust frameworks and usage control show promise, these advancements suffer from **insufficient empirical validation**, leaving significant questions about their operational effectiveness.
- Future research should prioritize **integrated sovereignty architectures** that systematically connect identity management, trust frameworks, and usage control within cohesive, verifiable policy enforcement systems.

5.5. RQ5: What is the coverage, technical novelty, and interrelation of Data Value Creation Enablers in data space research?

To address RQ5, we build on *Facet 1 – Building Blocks* and *Facet 3 – Technical Novelty*, focusing on the three components of *Data Value Creation Enablers*: *Data Offering*, *Publication and Discovery*, and *Value Creation Services*.

Coverage: Fig. 15 (top, outer pie chart) reveals a pronounced imbalance in research focus. *Data Value Creation Enablers* dominate academic contributions (72.2%), while *Data Offering* accounts for 14.8% and *Publication and Discovery* for just 13.0%. This contrasts with the IDSA Data Spaces Radar, where *Data Offering* (28.9%) and *Publication and Discovery* (27.4%) receive greater emphasis,[34] as shown in Table 15.

Technical novelty: The level of innovation among components is limited (see Fig. 15 top, inner pie chart). *Data Offering* and *Publication and Discovery* both show high reuse rates (76.5% and 86.7%), heavily relying on semantic web standards; primarily DCAT for asset descriptions, RDF for metadata representation, and SPARQL for query-based discovery. This pattern reflects a strategy prioritizing interoperability with existing semantic infrastructures while minimizing implementation barriers. Similarly, *Value Creation Services* also show high reuse (34.9%). Notable contributions include connector-integrated data applications for in-situ data processing, architectures for DT integration, and data marketplaces for asset discovery and monetization. However, over half of the studies in this category fall under the *NA* classification (54.2%), often describing use cases or domain-specific instantiations without introducing technical mechanisms.

[34] The IDSA Data Spaces Radar does not directly measure *Value Creation Services* but instead tracks *Marketplaces and Usage Accounting* (10.5%), following the categorization of initial versions of the DSSC Blueprint.

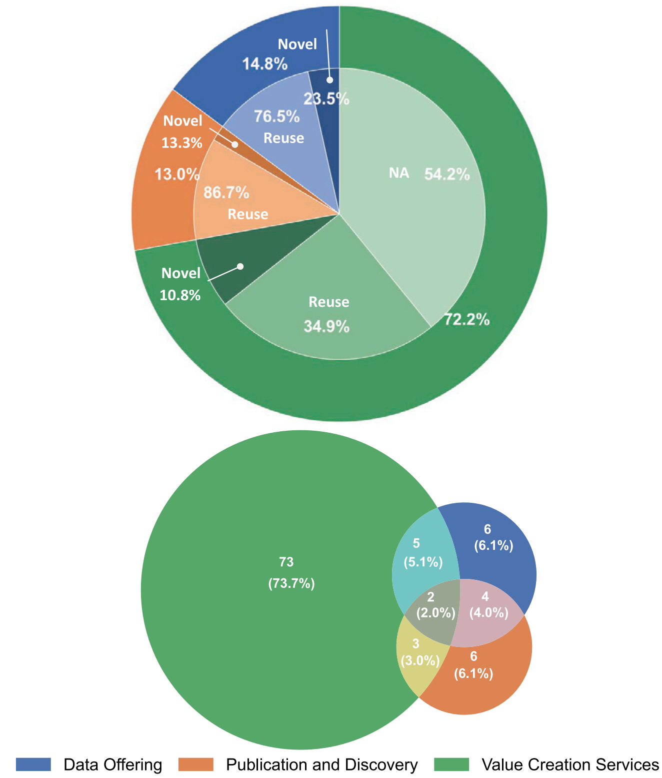

Fig. 15. *Data Value Creation Enablers* analysis: coverage and technical novelty (top), and component relationships (bottom).

Relationships across components: Co-occurrence analysis (see Fig. 15 bottom Venn diagram) shows that only 2 studies comprehensively address all three categories simultaneously, and integration between pairs is rare (fewer than 5 studies each). This fragmentation suggests that despite attention to individual categories, their integration within cohesive architectures remains unexplored. The absence of joint approaches across offering, discovery, and service layers limits the development of cohesive data value chains in data spaces.

Insights: Analysis of coverage, technical novelty, and interrelation of *Data Value Creation Enablers* yields these findings:

- **Research focus diverges from industry needs.** Academic work centers on *Value Creation Services*, while industry emphasizes *Data Offering* and *Publication and Discovery*, revealing a gap between application-driven research and infrastructural readiness.
- High *Reuse and Integration* rates reflect **convergence around the use of semantic web technologies**.
- Opportunities exist for incorporating **privacy-preserving computation paradigms** in data space research, including compute-to-data approaches, TEEs, and decentralized analytics, underrepresented technologies that enable value extraction while maintaining sovereignty.

Table 15
Academic vs. industrial (IDSA Data Spaces Radar) focus comparison for *Data Value Creation Enablers* components.

Component	Academic	Industrial	Gap
Data offering	14.8%	28.9%	Industrial +14.1%
Pub. and discovery	13.0%	27.4%	Industrial +14.4%
Value creation services	72.2%	10.5%	Academic +61,7%

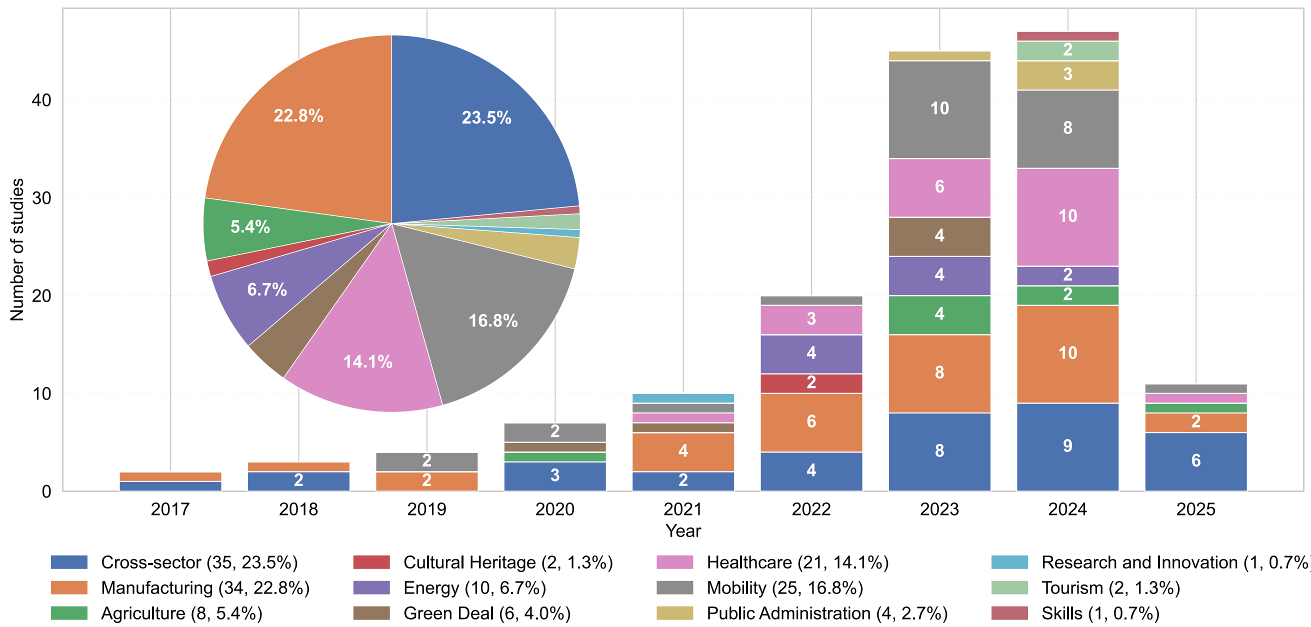

Fig. 16. Distribution of primary studies by sector over time.

- Few studies address all three value creation components, highlighting the need for **integrated architectures** to create complete data value chains within data spaces.

5.6. RQ6: Which sectors received most attention, and how is this attention evolving?

To address RQ6 we analyze the distribution of studies across economic sectors using *Facet 4 - Sector*, reflecting the alignment of research efforts with sector-specific needs.

Coverage: Fig. 16 shows that *manufacturing* (22.8%) and *cross-sector* approaches (23.5%) dominate data space research, followed by *mobility* (16.8%) and *healthcare* (14.1%). This distribution broadly aligns with the industrial trends captured in the IDSA Data Spaces Radar, which similarly identifies *manufacturing* (24.7%) as a leading sector, followed by *mobility* (12.1%) and *energy* (11,1%).[35] The dominance of manufacturing reflects the historical roots of the IDSA, originally established as the Industrial Data Spaces Association, with an early emphasis on industrial use cases.

Notable research gaps exist in some of the 14 sectors outlined in the EU's data spaces strategy [5]. *Language*, *finance*, and *media* data spaces are entirely absent from our primary studies, highlighting both sector-specific implementation challenges and significant opportunities for future research.

Temporal evolution: The temporal analysis reveals that early studies (2017–2019) remained limited and primarily focused on generic frameworks and manufacturing applications, reflecting initial data space conceptualizations.

Significant growth and diversification began in 2021, with notable sector-specific trends emerging. *Manufacturing* maintained consistent growth, aligning with the maturation of initiatives like Catena-X for automotive supply chains. *Mobility* research accelerated sharply in 2022–2024, coinciding with the European Commission's Communication on creating a common EMDS [218], which established a policy framework for cross-border mobility data sharing. Similarly, *healthcare* publications increased following the EHDS Regulation [219], proposed in 2022 and published in 2025, particularly in areas addressing privacy concerns and cross-border patient data exchange. These regulatory initiatives have shaped research priorities across sectors, confirming [220] observations that sectors develop governance approaches tailored to their specific regulatory environments.

Based on observed growth trajectories, we anticipate continued growth in *mobility* and *healthcare* research, with emerging interest in *cultural heritage*, *green deal* and *agriculture* as sustainability gains priority. Cross-sectoral interoperability will become a priority as implementations mature and increasingly seek value from data across sector boundaries.

Building blocks-sector associations: Fig. 17 highlights how sectors align with technical building blocks and research type. *Manufacturing* leads in both volume and breadth, especially in *Data Value Creation Enablers* (28 studies), *Data Interoperability* (23 studies), with more *solution proposals* (29) than in other sectors; likely reflecting its emphasis on supply chain integration. *Mobility* follows with strong activity in *Data Value Creation Enablers* (18) and *Data Interoperability* (16), with 15 *validation studies*, driven by real-time data requirements and multi-stakeholder coordination. *Healthcare* concentrates on *Data Sovereignty* (10) and *solution proposals* (6), consistent with its strict regulatory constraints and focus on patient data privacy.

Insights: Analysis of data spaces sectors of application and their temporal evolution reveals these findings:

- *Manufacturing* dominance (22.8%) reflects the industrial origins of data spaces, yet increasing diversification indicates maturation toward broader ecosystem approaches.
- Temporal correlation between regulatory initiatives and subsequent research spikes demonstrates the critical influence of policy frameworks in directing technical attention.
- A significant proportion of *cross-sector* studies (23.5%) indicates ongoing development of foundational technologies essential for future cross-domain interoperability.
- Disparities persist between dominant sectors and underrepresented domains like *cultural heritage* (1.3%), indicating opportunities for targeted research initiatives.

[35] Data Spaces Radar uses granular classification, reporting *Smart Cities* (9.5%) and *Logistics* (7.4%) separately, whereas in our classification schema these are included within *Mobility* and *Manufacturing* sectors respectively.

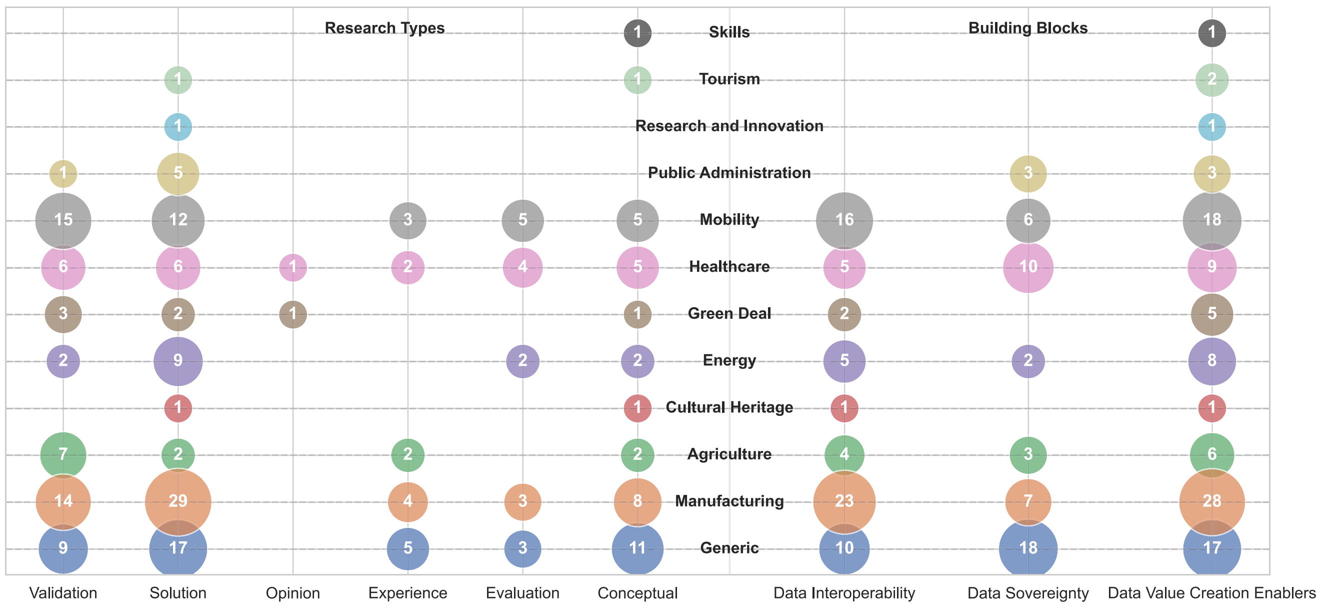

Fig. 17. Mapping of sectors across research type and building blocks.

6. Conclusions

Data spaces are reshaping data sharing and governance across sectors by emphasizing sovereignty, interoperability, and trust. Yet, the field remains fragmented, with varied implementations, inconsistent terminology, and uneven maturity across technical and domain-specific dimensions. To address this, we conducted a SMS of 149 peer-reviewed studies, representing the most comprehensive synthesis of data space research to date.

Our analysis addresses six RQs that examine both the technical foundations and sectoral applications of data spaces.

RQ1: Methodological maturity and technical novelty. The field is still maturing, with 64.4% of studies falling into the solution proposal or validation phases, and only 5.4% offering concrete evaluations. Technical novelty is mostly architectural or conceptual, with limited empirical or system-level implementations. This highlights the need for more applied research and real-world validations.

RQ2: Building blocks coverage, evolution and interrelation. *Data Value Creation Enablers* dominate the landscape (46.3%), followed by *Data Interoperability* (30.8%) and *Data Sovereignty* (22.9%). Only 34.9% of studies cover multiple building blocks, indicating limited integration. Recent years show growing attention toward*Data Sovereignty* and *Data Value Creation*, though holistic approaches remain scarce.

RQ3: Data interoperability. *Data Models* (40%), *Data Exchange* (41.3%), and *Provenance and Traceability* (18.7%). Semantic interoperability is widely addressed, but innovation is incremental and often based on standard reuse.

RQ4: Data sovereignty. *Identity Management* (26.5%), Trust Framework (32.4%), and *Usage Control* (41.2%). Research is rich in conceptual models, but practical implementations are still emerging. Integration with other building blocks is minimal, reflecting a fragmented approach.

RQ5: Data value creation enablers. Dominated by *Value Creation Services* (72.2%), followed by *Data Offering* (14.8%) and *Publication and Discovery* (13%). Most studies rely on existing technologies, with limited novelty.

RQ6: Sectors of application. *Manufacturing* leads in adoption 22.8%, followed by *cross-sector* approaches (23.5%), *mobility* (16.8%), *healthcare* (14.1%), and *energy* (6.7%). Sectoral implementations often adapt generic architectures with sector-specific extensions. Cross-sector integration and comparative analysis are still limited but emerging.

Overall, our study reveals that data space research is active and expanding but still fragmented and at an early stage of maturity. While value creation is well-covered, interoperability and sovereignty components are gaining ground, though often developed in isolation. The limited integration across building blocks indicates a need for more holistic approaches.

While this SMS has focused primarily on the technical dimensions of data spaces, future research should also address the equally critical aspects of governance and business models. These dimensions are essential to understanding the paradigm shift data spaces propose in data management, particularly regarding data ownership and value distribution. The current technology-driven trajectory, as identified in RQ1 through the lack of real-world validations and integrated approaches, suggests a gap in aligning technical developments with viable governance frameworks and scalable business strategies. A systematic review that maps the evolving landscape of governance mechanisms and business enablers would therefore be a valuable complement to the present study, helping to bridge the gap between conceptual promise and operational reality.

We hope this work serves as a foundation for more integrated, mature and implementation-driven efforts in the design and deployment of trustworthy data spaces across sectors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The complete dataset of primary studies, including facet classifications and detailed metadata, is publicly available in the repository referenced in the manuscript[2]. The data supports independent verification of results, replication of analyses, and extension of this research.

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