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Intelligent Discovery and Governance of Healthcare Data Assets Through AI-Powered Catalog Architectures

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ABSTRACT: Healthcare systems store diverse clinical, operational, and research data in often-overlapping but poorly linked silos. Patient privacy and related regulations complicate data-sharing agreements and inhibit large-scale analytics. Data catalogs—the systems that enable search, browse, and discoverability of digital content across organizations—are too rarely deployed for healthcare data. AI-powered solutions have been proposed for discovery of data in many sectors. If realized, such approaches will facilitate faster access to healthcare data, compliance with regulations, and secure data-sharing agreements with proper oversight.

Data discovery in healthcare is challenging, yet essential for both clinical operations and research. The diverse roles of prospective data consumers need to be supported: data scientists, data stewards, data custodians, clinical investigators, translational faculties, and data producers. Metadata management is a critical component of successful data discovery, encompassing both population with consistent schemas and standards, and enrichment of quality, provenance, technical, and other metadata for findability. AI techniques useful for data cataloging across other sectors—including machine learning, natural language processing, and entity recognition—are applicable to the healthcare domain.

KEYWORDS: Data Catalog, Healthcare, Discovery, Governance, Metadata Management, Enrichment, Data Quality, Natural Language Processing Data catalogs enable the discovery of data assets across organizational silos and enhance data governance through the management of data provenance, data lineage, and metadata quality.

I. INTRODUCTION

The digitalization of health care organizations has enabled the generation of large amounts of clinical and research datasets that hold the potential to advance patient care and improve research outcomes. However, the processes underlying storage and access in contemporary health care environments potentially hinder the reuse and discoverability of datasets. Consequently, various AI-powered systems that form part of the data ecosystem of health care organizations have been proposed with the goal of improving data discoverability and facilitating data governance. AI-based data catalog systems represent one such class of systems that, when populated with the necessary metadata, support self-service data discovery. By improving metadata completeness, data catalogs can also assist data stewards in their governance responsibilities.

A data catalog acts as a central repository that enables users, typically analysts and data scientists, to discover data in a straightforward and self-service manner. Such systems have mostly focused on nonhealth care data, but catalog-enabled discovery is becoming increasingly relevant in health care contexts. Due to the complexity of health care data and their high-risk nature, ensuring that data can be found, understood, and obtained by users in compliance with relevant legislation — such as the Health Insurance Portability and Accountability Act of 1996 — is critical for real-world impact. Data governance is therefore another fundamental challenge in health care settings, as organizations must ensure that the right people can access the right data at the right time and in the right context, with an adequate understanding of the data and their limitations.

Data catalogs are emerging as essential infrastructure in modern health care data ecosystems, providing a centralized, searchable environment where analysts, clinicians, and data scientists can efficiently discover and understand available data assets. While these tools have historically been designed for non–health care domains, their adoption in clinical and

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biomedical settings is accelerating due to the growing volume, variety, and complexity of health data. Unlike many other industries, health care data are highly heterogeneous, sensitive, and tightly regulated, requiring discovery mechanisms that go beyond simple indexing to include rich metadata, standardized terminologies, data provenance, and contextual documentation. At the same time, effective data governance must be tightly integrated with catalog functionality to ensure compliance with regulations such as HIPAA, enforce role-based access controls, and provide transparent auditability. By aligning data discovery with governance, health care organizations can ensure that users not only find the data they need but also understand its quality, limitations, and appropriate use, thereby enabling responsible analytics and fostering trust in data-driven decision-making.AI-based Data Catalog Systems merge the knowledge of the clinical domain with the technical data analysis and Cloud implementation expertise and thereby allow AI-powered data catalog for Health Data Discovery and Governance.

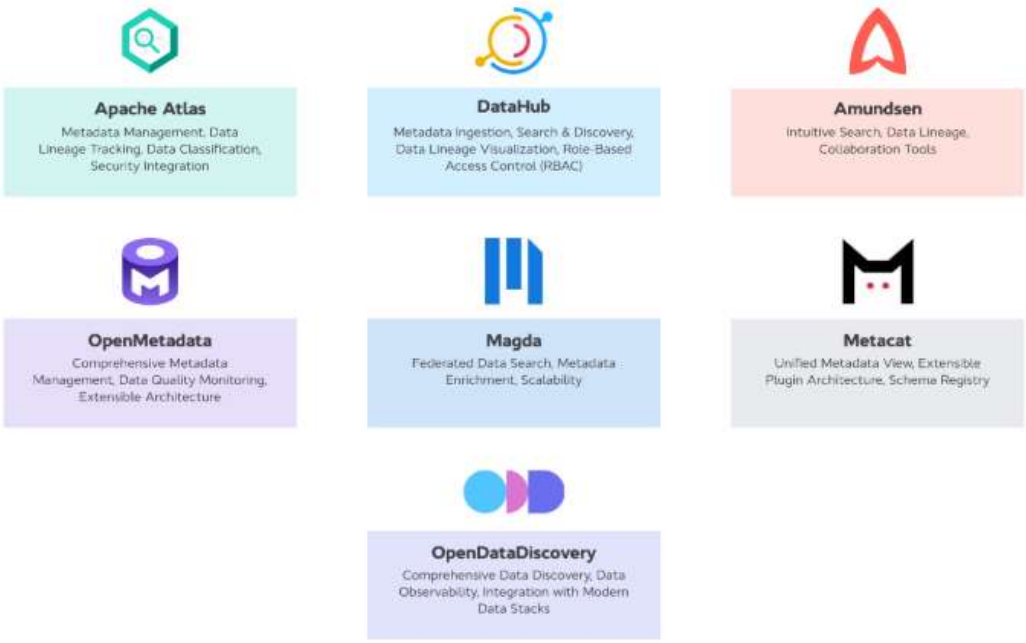


Fig 1: Open-Source Data Catalogs

1.1. Background and Significance

Healthcare data remains among the most complex and fastest-growing elements of modern life. Modern medical devices generate rich records. Clinical trials collect troves of richly abstracted longitudinal data. Social networks can serve clinical needs from predicting patients' symptoms and offering support to early detection of infectious disease outbreaks. The rise of Internet of Medical Things adds data from hundreds of millions of implantable devices and wearables. Nevertheless, data at this scale matter very little without the correct underlying infrastructure to transform raw bits into clinically meaningful information that can be deployed to improve patient care and research. A major challenge lies in decision makers being incapable of understanding nor even finding the data that exists. Much of the data supported in hospitals is still tamed by needed interdisciplinary collaboration between several fields like, medicine, statistics, computer engineering.

Metadata-driven data catalogs and data stewardship with associated community interaction can help break through data silos as a result of data primary being shared but not used for research. However, sensitive patient-identifiable information contained in such resources imposes major restrictions on searching for and accessing the stored data. The adoption of Artificial Intelligence (AI) and Machine Learning (ML) models can help with the analysis of these data. The aid of rules and filters can further allow specific patients' clinical data to be discovered and used when required.

Equation 1: Completeness of required metadata

Let $R \subseteq \{1, \dots, k\}$be the index set of **required** metadata fields.

Define an indicator:

$$I_j(d) = \begin{cases} 1 & \text{if field } f_j \text{ is present and non-empty for } d \\ 0 & \text{otherwise} \end{cases}$$

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Step-by-step derivation

1. Count filled required fields: $\sum_{j \in R} I_j\,(d)$
2. Total required fields: $|\,R\,|$
3. Normalize to $[0, 1]$:

$$\text{Completeness}(d) = \frac{1}{|\,R\,|} \sum_{j \in R} I_j\,(d)$$

II. FOUNDATIONS OF AI-POWERED DATA CATALOGS

A data catalog organizes, manages, and maintains metadata on an organization's data ecosystem and its many data elements and assets, allowing users to find, understand, and use these resources. The architecture comprises three main components: a storage component, for metadata and catalog-related data; a metadata management and enrichment service, for creating and maintaining a rich set of metadata; and a discovery/usage component, for locating and accessing data elements. Healthcare data catalogs differ from corresponding resources in other domains by providing support for sensitive domain- and user-specific requirements. Cataloging for sensitive use cases requires additional capabilities focused on privacy-preserving access to sensitive data elements, modeling and controlling compliance risks during data access and use, and ensuring compliance with regulatory data management guidance.

AI-powered data catalogs represent a solution to the challenges associated with finding and accessing data in healthcare data ecosystems. A growing number of organizations are now adopting AI-powered data catalogs to ease the search for data, automate tagging and classification, capture data lineage, and present information in user-friendly interfaces. These catalogs are not just repositories of metadata—there is considerable and largely unrecognized innovation in the practical use of AI to create meaningful, contextualized, and coherent catalog metadata bases that enhance the management of sensitive data.



Fig 2: Foundations of AI-Powered Data Catalogs

2.1. Definitions and scope

Data catalogs are intended to organize an index of data assets to help users discover data relevant for their needs. The traditional data catalog comprises a searchable index of structured metadata together with a shallow description of the data set and general availability informaton. Enriched metadata is foundational to improving the discoverability of data assets. Metadata management and enrichment elevates both the accuracy of search results and the success of users in finding data relevant to their data discovery workflows.

The management of metadata in a catalog system encompasses the design, population, maintenance, and exploration of the metadata schema. support for metadata is often narrowly focused on the schema itself. For structured data, processes have been developed to define the metadata schema, detect the data types of columns, and standardize column names. In certain domains, such as clinical and biomedical research, the community has advanced collaborations to develop

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domain-specific metadata standards. Within the catalog, these schemas are often used as the basis for populating the catalog and for the facility of search. Additional metadata information is contributed by users, data owners, and data stewards through a tagging mechanism. Data custodians may leverage catalog services to capture the lineage of data assets. External data assessments and automated tools can augment the metadata content with information related to data quality, such as data freshness, completeness, and accuracy.

Equation 2: Freshness score (time decay)
Let:

- t_{now} = current time
- $t_{\text{update}}(d)$ = last update timestamp
- $\Delta t = t_{\text{now}} - t_{\text{update}}(d)$
- τ = acceptable "half-life" (days)

A common freshness curve is exponential decay:

Step-by-step
1. Set decay rate $\lambda = \ln(2)/\tau$ (so score halves every τ)
2. Apply exponential decay:

$$\text{Freshness}(d) = e^{-\lambda \Delta t}$$

Suppose n validation checks run on dataset d, and p pass.

Step-by-step
1. Pass proportion: p/n

$$\text{Accuracy}(d) = \frac{p}{n}$$

Weight the components:

- completeness C
- freshness F
- accuracy A
- provenance coverage P
- lineage coverage L

Step-by-step
1. Choose weights $w_C, w_F, w_A, w_P, w_L \geq 0$
2. Normalize weights: $w_C + \cdots + w_L = 1$
3. Weighted sum:

$$\text{Readiness}(d) = w_C C(d) + w_F F(d) + w_A A(d) + w_P P(d) + w_L L(d)$$

III. DATA DISCOVERY IN HEALTHCARE ENVIRONMENTS

The need for data discovery in healthcare is evident across the ecosystem. Recognizing and finding the data required to fulfill a task is the first step toward a solution. The prerequisites, however, diverge according to the actor's role. In the discovery-to-usage flow, researchers and data scientists search for data sets that satisfy their upcoming projects, while technical staff query for data for analytics, data science models, or pipeline creation. Clinical data scientists seek data to prototype models, while clinicians seek data for specific patients or groups in clinical research processes.

User-Facing Search and Discovery Natural language search that caters for patients, cohorts, and de-identified data has seen interest. Curation is limited to the desirable combination of a term and visualization that helps fulfill queries. A search engine back end for findability is an obvious complement to metadata standardization efforts such as OMOP CDM and similar international initiatives. Integration into clinical and research workflows is important for an acceptablerake and revisit rate. Queries on the fly, however, risk being performed without mature understanding of the data, despite resulting in data for which lineage information is not yet fully functional.

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Fig 3: Data Discovery in Healthcare Environments

3.1. Metadata management and enrichment

Managing and enriching metadata is a significant undertaking for many organizations. Several aspects need special attention. First, health data is built on a complex framework that defines the data model, identifiers such as pathology department codes, the value domain, and the relationship between the data entity. The Health Level 7 (HL7) administration body aims to create interoperability between EHR data in health institutions, patients' data, contact data, and laboratory data. A similar initiative is undertaken by the Global Partnership for Artificial Intelligence (GPAI), aiming to provide the working group with artificial intelligence capabilities for the creation of agency laboratories.

Second, a large organization operates as several different legal entities. The jurisdictions, the languages, and the conditions in each country explicitly require the labeling of the identity and contact information of the data. Thus, a data stewardship schema modeled from the Object Metadata Exchange Format (OMEX-Format) needs to adhere to the Local Health Authority and Regional Authority requirements and mandate the labeling of data and its custodians. Third, insufficient text describes most datasets, resulting in both data being inaccessible during the search and a greater scramble for use. Text may either provide an overview of data or delineate the specialized usage of the data. Automated tagging of large amounts of text using machine learning tools may stimulate an increase of data description.

Enrichment pipelines that consume metadata provenance information and also capture metadata about data lineage are essential for a large hospital that manages data from first-level hospitals. Such hospitals serve as a control point to detect abnormal cases and also provide populations of routine data for research, follow-up, and advanced modeling. To validate made samples, a network of hospitals acts as a quality control detector.

Capturing lineage information is thus crucial for the hospital that steers those hospitals. The metadata model records the behavioral state of data elements in an audit process-based manner, detecting and validating time-stamped changes that ward off data without approval. That ensures the reputation of the data and their foundation for decision-making processes.

Equation 3: Semantic search with embeddings (matches paper's "meta-embedding / semantic discovery")
Let:

- $e_q \in \mathbb{R}^p$ be the query embedding
- $e_d \in \mathbb{R}^p$ be dataset embedding (from metadata + schema + tags)

Step-by-step

1. Dot product: $e_q \cdot e_d = \sum_{i=1}^{p} e_{q,i}\, e_{d,i}$
2. Norms: $\| e_q \| = \sqrt{\sum_i e_{q,i}^2}$, $\| e_d \| = \sqrt{\sum_i e_{d,i}^2}$
3. Normalize:

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$$\cos(e_q, e_d) = \frac{e_q \cdot e_d}{\| e_q \| \ \| e_d \|}$$

IV. AI TECHNIQUES FOR CATALOGING HEALTHCARE DATA

Healthcare data exhibit unique characteristics and structures that must be captured for added-value discovery and usage. AI and machine-learning algorithms are extensively employed to process unstructured and semi-structured information. Such techniques can also help automate the classification of data assets in catalog systems and serve to expose clinical and associated data well beyond the obvious keywords present in the metadata. A range of widely applied models, including meta-embedding, autoencoder, and Siamese neural architecture approaches, may be leveraged to enrich the discoverability of healthcare data, enabling connections to other forms of managed metadata such as entity definitions. Keywords, tags, and focused topics generated through NLP methods may also be employed to model deeper explorations into complementary repositories such as image, video, and signal data collections.

Natural language processing facilitates the production of indices that can be searched effectively without reliance on exact-match queries. Leveraging detailed metadata descriptions, NLP services expose data assets using standard clinical terminologies, biological ontologies, existing entity databases, and special-purpose clinical and research ontologies that align entity relations across multimodal data. NLP supports the linking of these clinical terms in both general and context-specific forms to cataloged data and any accompanying metadata. On top of linking semantically meaningful ontology terms from the resource web, entity linking enables queries not just via textentries or phrases but also through intelligently built entity representations that guide users in a more focused direction. This process creates an interaction layer between users, clinical entities, relationships, and data assets in the catalog.

Natural language processing (NLP) plays a pivotal role in transforming how users discover and interact with complex clinical and research data by enabling the creation of semantically rich, searchable indices that move beyond traditional exact-match keyword approaches. By harnessing detailed metadata descriptions, NLP services map data assets to standardized clinical terminologies, biological ontologies, curated entity databases, and domain-specific clinical and research ontologies, ensuring consistent representation and interoperability across diverse datasets. This semantic alignment allows entities and their relationships to be recognized across multimodal sources—such as text, images, genomic data, and structured records—while preserving both general meanings and context-specific nuances. Through entity linking, users can query not only with free-text phrases but also through intelligently constructed entity representations that encapsulate concepts, synonyms, hierarchies, and relationships. As a result, NLP establishes a dynamic interaction layer that connects users, clinical entities, their interdependencies, and cataloged data assets, ultimately enabling more precise, intuitive, and insight-driven exploration of biomedical information.



Fig 4: AI Techniques for Cataloging Healthcare Data

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4.1. Natural language processing and entity recognition

Natural language processing (NLP) techniques, including large language models, extract meaning from unstructured text, enabling search and information retrieval. These methods help classify and categorize clinical documents. Parsing textual descriptions of data assets supports dataset discovery. Mapping to clinical terminologies, including SNOMED CT, UMLS, MedDRA, and LOINC, permits richer, lower-overhead searches. Clinical terminologies evolve over time; ontologies and knowledge graphs support the development of new terms with links to older equivalents. Mapping endpoints to standard resources in RDF form allows the use of existing vocabulary alignment packages. NLP-based entity linking approaches connect terms in clinical texts to metadata and available data assets. Entity recognition enhances information on available data as a by-product of indexing the underlying text or categories of data in text from/to metadata description generation. A rich text tagging pipeline can connect a large share of clinical records to their concepts.

Equation 4: Hybrid retrieval (keyword + embeddings)

A practical AI catalog often combines both:

- lexical score $S_L = \text{BM25}(q, d)$
- semantic score $S_S = \cos(e_q, e_d)$

Because the ranges differ, normalize both to $[0, 1]$using min–max over candidate set $\mathcal{C}$:

$$\tilde{S}(d) = \frac{S(d) - \min_{x \in \mathcal{C}} S(x)}{\max_{x \in \mathcal{C}} S(x) - \min_{x \in \mathcal{C}} S(x)}$$

Then combine:

Step-by-step

1. Normalize lexical: $\tilde{S}_L(d)$
2. Normalize semantic: $\tilde{S}_S(d)$
3. Weighted fusion:

$$S_{\text{hybrid}}(d) = \alpha\, \tilde{S}_L(d) + (1 - \alpha)\, \tilde{S}_S(d) \text{where } 0 \le \alpha \le 1$$

V. DATA GOVERNANCE, COMPLIANCE, AND RISK MANAGEMENT

Effective governance and risk management are also essential for proper cataloging of user-generated data—particularly sensitive data governed by various regulations and stewardship principles. An instantiation of the data governance and risk management framework presented in the seminal work on policies for data ecosystems is effective for describing cataloging systems in general, and can be used to guide management of a data catalog that organizes and provides discoverability of compliance-sensitive healthcare data.

The data governance structure encompasses the policy-setting organizations, the communities of stakeholders who are both responsible and accountable for defining stewardship standards and controls, and the major pieces of legislation and the risk controls prescribed by these standards. EU General Data Protection Regulation (GDPR), US Health Insurance Portability and Accountability Act (HIPAA), ISO/IEC 23988:2022, and the FAIR principles, especially the implementing guidance for the Principles of Data Stewardship, are important for catalog management because they define the requirements for data that can be accessed by users grouped in communities, such as research projects, and hosted on platforms such as research infrastructures.

Equation 5: NLP entity recognition/linking metrics (precision/recall/F1)

Let:

- TP=true positives, FP=false positives, FN=false negatives

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

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Step-by-step

1. Harmonic mean:

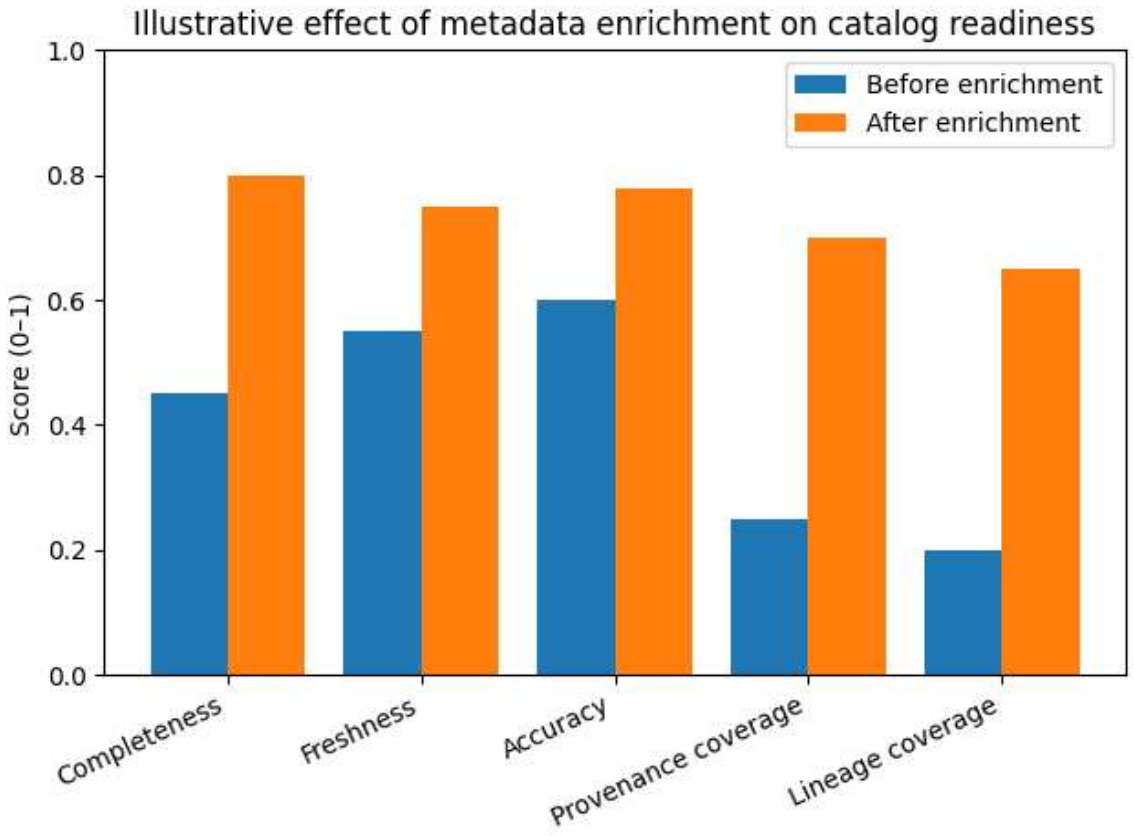
$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

5.1. Regulatory frameworks and standards

Healthcare organizations are subject to an array of regulatory mandates that govern the handling of sensitive data. The Health Insurance Portability and Accountability Act of 1996 (HIPAA) Security Rule deals with the protection of electronic patient information, and states that institutions must implement "physical safeguards for all work stations that access ePHI" and "controls that limit physical access to […] data warehouses." The General Data Protection Regulation (GDPR) seeks to protect all user data that is transmitted through the European Union (EU).

Data catalog tools can facilitate compliance with these and other requirements. For example, electronic healthcare records with restricted access mapped to these access control policies can be flagged in the catalog, which can then expose only data accessible for a pipeline given the identity of the person running the pipeline. If a data request for research utilization has been approved and is expected to be considered common, the catalog can provide additional visibility and expose common datasets with such permissions. In the case of auditing and accountability, the capture of data lineage has been identified as an important traceability criterion in the implementation of governance and risk management frameworks for information technology, such as ISO 38500.

At the data service or query level, provenance information can also be leveraged for auditing system behavior and risk management. The audit specification "ISO/IEC 23988:2016: Information technology — Security techniques — Audit and risk management" provides guidance on the management of data for security measurements and seems applicable for cataloged data as well. The Findable, Accessible, Interoperable and Reusable (FAIR) principles encourage the publication and sharing of datasets and assign clear ownership for data usage regimes. Data stewardship seems critical for achieving these objectives and represents a key dimension for enabling data discoverability. The availability of mature data catalogs is expected to improve compliance with these regulations and standards.



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VI. DATA DISCOVERABILITY IN CLINICAL AND RESEARCH CONTEXTS

A data catalog built on an AI-enabled metadata management foundation can enhance the discoverability of healthcare data. By considering the clinical and research use cases to which data may be put, the catalog can support data search and retrieval in these areas. If supported by clinical and research workflows, the data catalog can make discoverability a natural by-product.

The use of clinical data for research is increasingly common, but such interactions are seldom supported by well-defined workflows, from the query to the retrieval of a dataset. Such workflows should encompass all stages of the interaction, including search, data access, usage control, and provenance validation. Enablement of these workflow stages creates a framework for evaluating data discoverability. Potent clinical search capabilities, combined with provenance validation and endorsed return policies, create an integrated clinical discovery process that assures risk control and audit capability.

Such support can similarly facilitate research discoverability; the catalog acts as an indexing system over the data landscape and can respond to broad keyword searches that span the discovery spectrum. When combined with support for data access requests, such keyword search capability fulfills the discoverability component of a research data lifecycle. Evaluation of these two facets of discoverability in two real-world settings supports that conclusion.

Actor / Role	Primary discovery need	Key catalog features
Data steward	Ensure metadata completeness; manage tags, standards, approvals	Stewardship workflows, quality dashboards, policy-aware publishing
Data custodian / platform engineer	Capture lineage/provenance; enforce access controls; monitor pipelines	Lineage graphs, RBAC/ABAC, audit logs, integration APIs
Data producer (source system owner)	Register new assets; provide correct descriptions, owners, update cadence	Easy onboarding, schema inference, templated metadata forms

Table : Roles and discovery needs (derived from the paper's roles section)

6.1. Clinical data discovery workflows

Workflow diagrams illustrate the main steps involved in a clinical data discovery request. The user submits a keyword query into the data catalog interface. Underlying search capabilities scan the cataloged metadata and enabled automatic classification signatures to surface data assets aligned with the semantic intent captured in the search. Next, supporting provenance data is examined to determine how the data were created and sampled, enabling trading off concerns for data credibility with data quality. The data steward role is central in facilitating the selection of data assets appropriate for patient privacy safeguarding and fulfilling the proposed query request. Standards-based data access mechanisms check access controls of the discovery processes to enforce restrictions and permissions conferred to the user.

In supporting clinical data discovery workflow for query expansion and follow-on discovery, the catalog surfaces likely-relevant datasets in the process. These matches enable follow-on searches, potentially combined with external sources of information, to explore additional aspects of the clinical condition. Because of emerging requirements for external validation of computational results, workflow systems in research and training environments use the catalog to expand searches into exploring replications of results in related populations. Discovery systems supporting the repurposing of clinical records—and full analysis and write-up workflows—leverage the catalog for direct access to data, provenance validation, and surveillance auditing.

VII. CONCLUSION

AI-powered data catalogs greatly alleviate the inherent challenge of discovering and accessing complex, distributed healthcare data while enhancing data governance, compliance, and management of data privacy, usefulness, and risk. Catalogs solve this data-discovery challenge by providing a sufficient level of automated, scalable, AI-assisted context for data search and understanding—context that remains critical, even with semester-long graduate courses in data stewardship practice, when exploring real data assets at-query time. AI techniques alike greatly induct the requisite metadata for supporting enterprise-wide data discoverability at the scale and speed needed. Nevertheless, with healthcare data ecosystems—a statement echoed by at least three prior catalogs—meta-enablement labels are not enough. Data customers, now trained at all levels of clinical expertise through three Tiers, also require clinical data and nomenclature

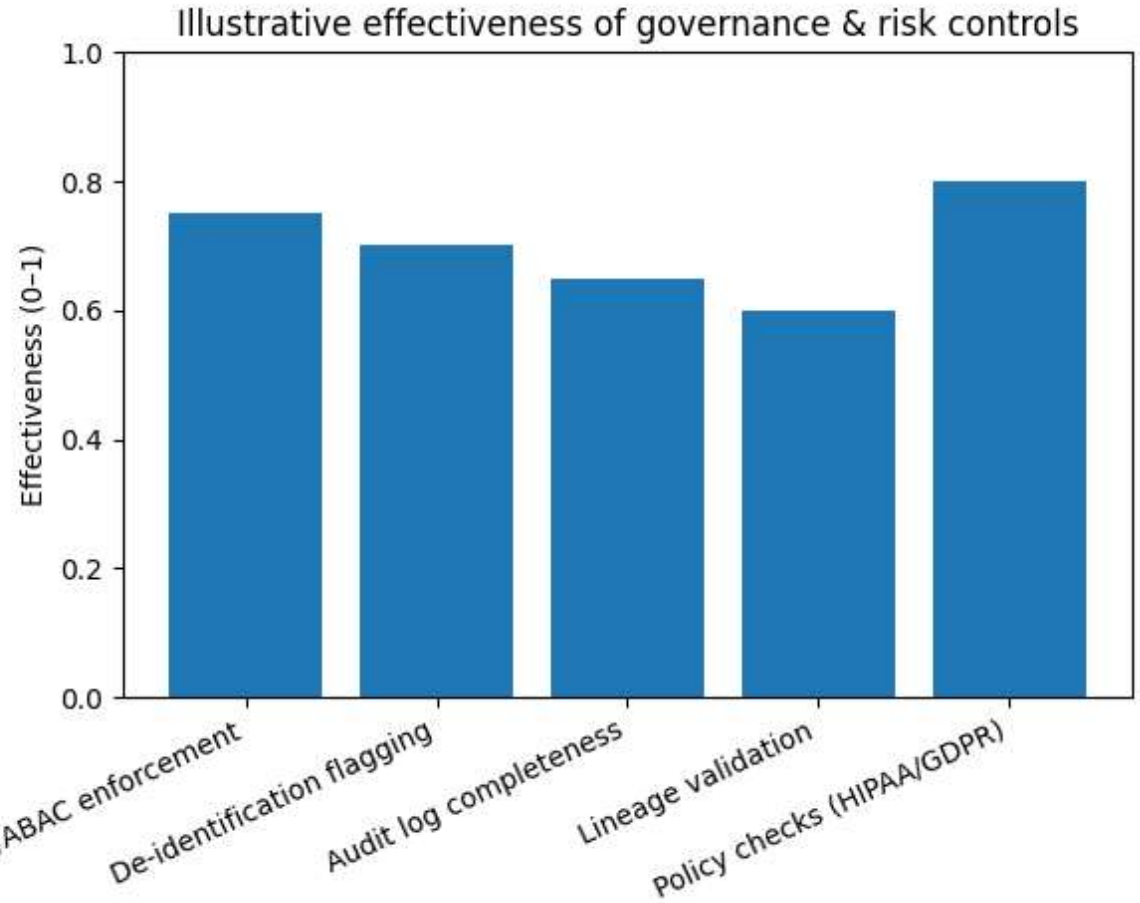
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contextualization to meaningfully browse datasets for considered access. For this user group, discovery in a dedicated search engine remains essential to facilitate at-query-time understanding.

The transparent and complete audit-trail records serve both clinical data managers, responsible for day-to-day data governance and management, and researchers, who apply their knowledge to ascertain data usefulness and risk—especially in these environments, yet again-the automation, log-parsing modeling, and structured-segment sniffing levels. Such controls in production and a facilities-driven approach yield a reuse and stewardship culture deeply aligned with the research domain, as expected. Moving up the maturity scale, narrated documentation of data-generation processes, data assets, and nodes exposed through a logic chain better signals enterprise compliance with HIPAA, GDPR, ISO/IEC 23988, and other regulatory frameworks. Given the absence of pain stickiness and GDPR compliance, risk structuring and management now appear as future work.



7.1. Future Directions

Advancing AI methods for data cataloging will strengthen healthcare data ecosystems and enable better services for end users. In particular, novel algorithms that integrate realistic clinical, cultural, and privacy challenges will return more powerful solutions. Solutions that focus on catalog quality, allowing most of the data to be either fine-grained or overlapping and how this can be accounted for in the cataloging process, will create more meaningful data catalogs.

Interoperability and exchange of catalog information across data stewards will pave the way for external search and discovery services. Proper data catalog governance is crucial to ensure support for the governance and compliance of the encapsulated data, especially as users retrieve and manipulate source data. Measuring the impact of data cataloging on the operational aspects of both research and clinical data stewardship–speed and accuracy of the information requested in the both activities, return on investment from the steward perspective, and user adoption–will help define if data catalog is just a trendy component of a data ecosystem or a utility that provides a real benefit in data discoverability and, ultimately, accessibility.

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Interoperability and seamless exchange of catalog information across data stewards form the foundation for a federated data ecosystem in which external search and discovery services can operate effectively. When data catalogs are governed with clear standards, policies, and accountability, they not only describe data assets but also actively support governance and compliance of the underlying datasets as they are accessed, reused, and transformed. Strong catalog governance ensures that metadata remains accurate, lineage is transparent, and usage constraints are enforced, reducing risk while enabling responsible data sharing. At the same time, systematic measurement of catalog impact—such as improvements in the speed and accuracy of information retrieval, return on investment from the steward perspective, and levels of user adoption—provides critical evidence of value. These metrics help determine whether a data catalog is merely a fashionable architectural component or a true utility that measurably enhances data discoverability and, ultimately, accessibility for both research and clinical operations.

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