Reimagining Clinical Data Architecture for Personalized Care

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Abstract

AI—driven precision medicine requires access to large amounts of clinical data together with detailed clinical annotations. Clinical data platforms support this need by integrating patient records, diagnostic data, and clinical research data within a collect—once, use—many approach. Rich patient records combined with scalable analytics platforms enable the reuse of clinical data for novel analyses. Such platforms create new clinical learning loops, allowing the delivery of genomic—guided precision therapeutics to more patients.

State—of—the—art clinical data platforms support dynamic, integrated clinical records, simplify cross—modality data collection, and facilitate the clinical adoption of AI technologies. The democratization of clinical data, imaging, and genomic data into open foundations allows the global research community to build foundation models that can later be adapted for clinic—specific contexts or for other clinical functions. Such foundation models offer rich transfer learning opportunities that reduce the cost of model training while increasing performance and addressing clinical bias. Emerging architectures—modelling techniques and privacy—preserving technologies address data interoperability challenges, supporting the creation of true population datasets at scale and at equal cost for all communities and demographics.

Keywords: Precision Medicine, Clinical Data, Data Platforms, Patient Records, Data Integration, Genomic Data, Clinical Annotations, Data Reuse, Learning Systems, Clinical Analytics, Foundation Models, Transfer Learning, Model Training, Data Interoperability, Privacy Preservation, Population Data, Medical Imaging, AI Healthcare, Data Democratization, Scalable Systems.

1. Introduction

Next-Generation clinical data platforms should be analyzed with an evidence-based, formal, and objective scholarly approach, focusing on architecture, standards, and impact on AI-powered precision medicine. Over the next decade, groundbreaking advances in Big Data and Applied AI, together with a decrease in the costs of data storage and processing, will provide unique opportunities to create next-generation clinical data platforms. These platforms should bring together both current and historical clinical data from multiple sources, naturally integrated into a common data model that supports AI applications across all clinical domains. Their design must follow a clear set of evolving principles, including the need for a granularity of detail and a level of data provenance that go well beyond that achieved in existing real-world evidence datasets.

The venue for academic discovery is also changing dramatically. Proliferating clinical research communities now collaborate to create Foundation Models—algorithmic systems that can be adapted and fine-tuned for many new applications. Growth in Automated Machine Learning (AutoML) tools, encompassing a MLOps lifecycle for ML, democratizes access and allows researchers to apply ML-driven approaches without specialized expertise. Foundation Models and AutoML tools reduce the cost of developing applied AI systems for precision medicine, thereby increasing the number of clinically useful solutions, but dependencies between these systems, together with the need for fairness and privacy, require new AI-based governance frameworks.

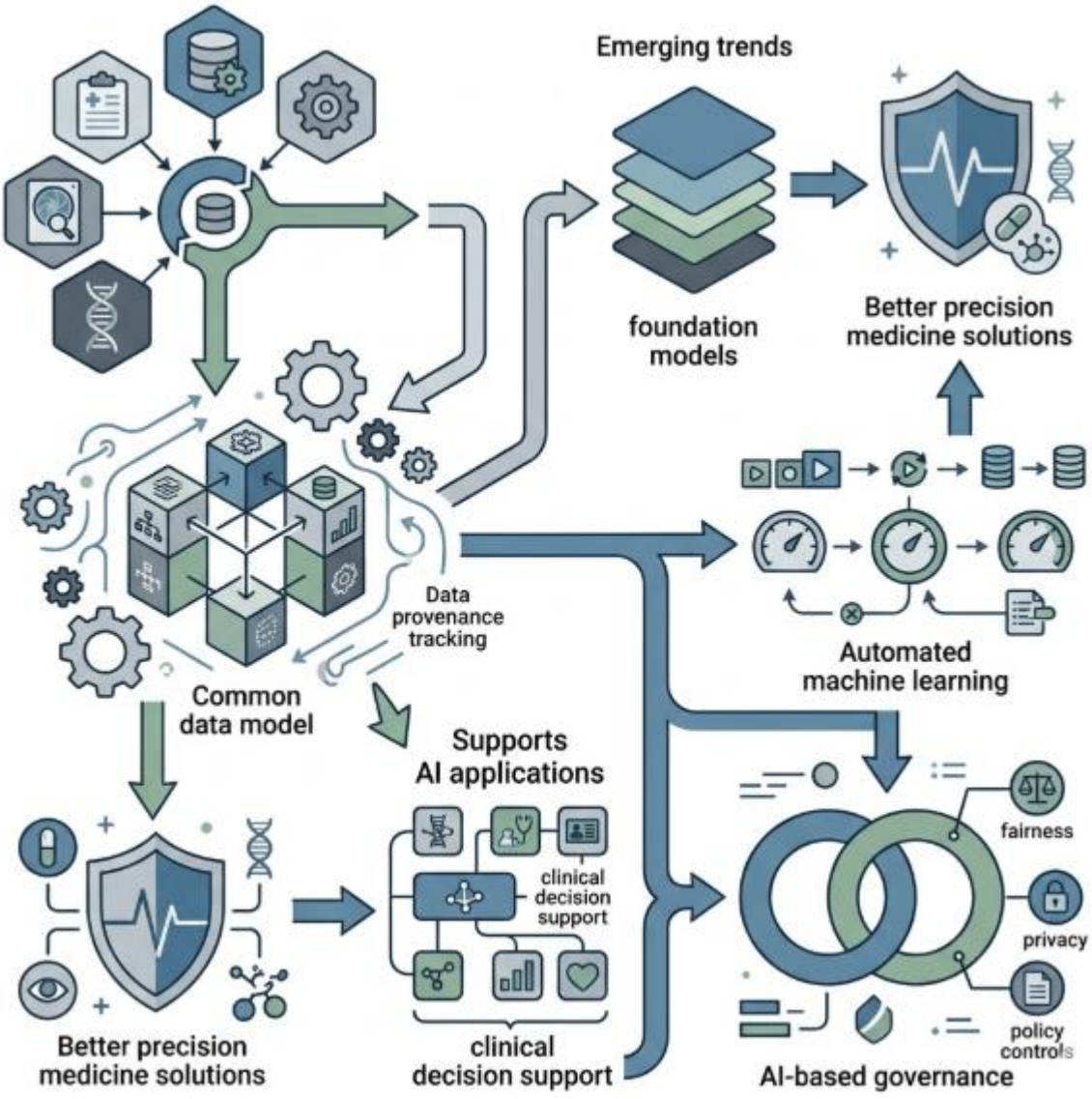

Fig 1: Architecting Integrity: Governance Frameworks for Foundation Models and AutoML in Next-Generation Clinical Data Ecosystems

2. Background and Motivation

Next-Generation clinical data platforms should be analyzed with an evidence-based, formal, and objective scholarly approach, focusing on architecture, standards, and impact on AI-powered precision medicine. AI holds significant promise to power precision medicine. This major AI-powered transformation of clinical care requires an associated major technology, process, and inter-organizational change in the platform of clinical data used to manage patients and run clinical trials. Evidence points to Next-Generation clinical data platforms that implement four core architectural principles, serve the needs of academic medical centers and healthcare systems engaged in clinical and translational research and personalized medicine, and facilitate the expansion of AI-generated clinical knowledge into clinical practice in an interoperable and equitable manner. Data generated, detected, acquired, or collected about patients throughout their life span—for example, clinical, genomic, transcriptomic, proteomic, metabolomic, imaging, biomechanical, microbiome, and exposure data—should be preserved as rich assets to systematically train, improve, adapt, customize, and personalize Foundation Models.

Nonprofit stakeholder organizations should facilitate this expansion and offer adoption pathways for Center for Scientific Review Study Sections to assess interventional or observational grant proposals. Not-for-profit organizations, federations, alliances, and initiatives whose shared purpose is a more effective, efficient, equitable, and safer healthcare ecosystem powered by AI-driven precision medicine should work collaboratively to establish policies, guidelines, and best practices for the implementation and use of Foundation Models in an AI-powered healthcare ecosystem. AI-generated knowledge has the potential to reduce the time required to translate scientific discoveries into life-saving therapeutic options. These discontinuities in the disease and treatment pathways create disparities between the individuals and communities who participate in the trials that lead to approvals of new treatments and those who cannot. It is now estimated that 37% of clinical trial populations in the United States are under-represented groups. The 2021 National Research Action Plan also highlights the importance of supporting health equity, reducing health disparities, ensuring diversity, and increasing representation within biomedical and behavioral research.

2.1. Vision and Rationale for AI-Driven Precision Medicine

AI-powered precision medicine represents the next generation of healthcare, guided by a common vision of seamless integration between clinical and technological domains. Achieving

this transformation requires the implementation of new clinical data platforms based on a set of architectural principles that preserve technology independence while satisfy-ing the needs of both clinical researchers and AI practitioners.

The healthcare domain is facing mounting pressure to deliver more effective solutions to treat patients. There is also increased scrutiny on the vast financial resources allocated annually to conduct these extensive clinical trials, with the projected costs of developing an approved new drug reaching $2.8 billion. Simultaneously, the pharmacogenomics concept has gained particular attention in the genomic-guided therapy space. While the COVID-19 pandemic highlighted an internal source of urgency to speed-up the drug discovery cycle by leveraging AI tools and technologies, it also exposed the bias limitations of traditional begging data approaches in addressing societal problem areas such as viral pandemics, climate change, and urban planning. To overcome these limitations, healthcare must evolve toward a new paradigm—AI-powered precision medicine—made possible by the emergence of a novel clinical data platform architecture that relies on identical AI models trained specifically for each domain or area of interest.

3. Methodology

A formal analysis of next-generation clinical data platforms supports their utility in AI-driven precision medicine. Core architectural elements are identified, supporting the design of a clinical data-processing platform that ingests, integrates, and models data from various sources including the EHR and translational science to support the development and deployment of Foundation Models for health care.

There is a pressing need for clinical data platforms that enable the emergence of Foundation Models for health care, including the integration and modeling of data spanning the diagnostic, therapeutic, and biological domains. These platforms support the development of clinical Foundation Models, which power a new wave of innovations spanning radiomics, genomics, and therapeutic response for major diseases. A data-processing platform that ingests, integrates, and models data from diverse sources, including clinical trials, the electronic health record, and translational-science endeavors, is necessary to empower a new generation of scalable AI-powered clinical Foundation Models.

3.1. Core Architectural Elements for AI-Driven Precision Medicine

AI-driven precision medicine relies on clinical data platforms that capture the entire data life cycle, organized within a layered data model. A process-oriented view that considers the full data life cycle, from ingestion and integration through preparation and serving, is essential to guide the choice of data model, representation, storage, and processing mechanisms. Core architectural elements are presented to derive an applicable data layer blueprint that meets the requirements of AI-powered precision medicine: scaling and automating the reproduction of existing, scientifically sound AI models for enabling Genomic-Guided Therapeutics and minimizing bias in clinical AI models. A modular, open-software architecture along with emergent technologies, spatially distributed data placement, and comprehensive process models of end-user data needs are key to enabling significant scaling of AI models and addressing fairness concerns.

AI models for clinical decision support and prediction of patient outcomes can provide significant clinical and commercial value, especially when they support precision medicine approaches, such as Genomic-Guided Therapeutics. Such AI models require a foundation data model that meets the data preparation and integration needs for the entire machine-learning life cycle: training, evaluation, and deployment. Population data is needed to train and evaluate the models, stratified cohorts for clinical deployment and decision support, and stratified cohorts with extensive external sources of information for bias analysis and mitigation. Scaling the reproduction of such assignable AI models for Genomic-Guided Therapeutics will address a significant clinical and economic gap in healthcare.

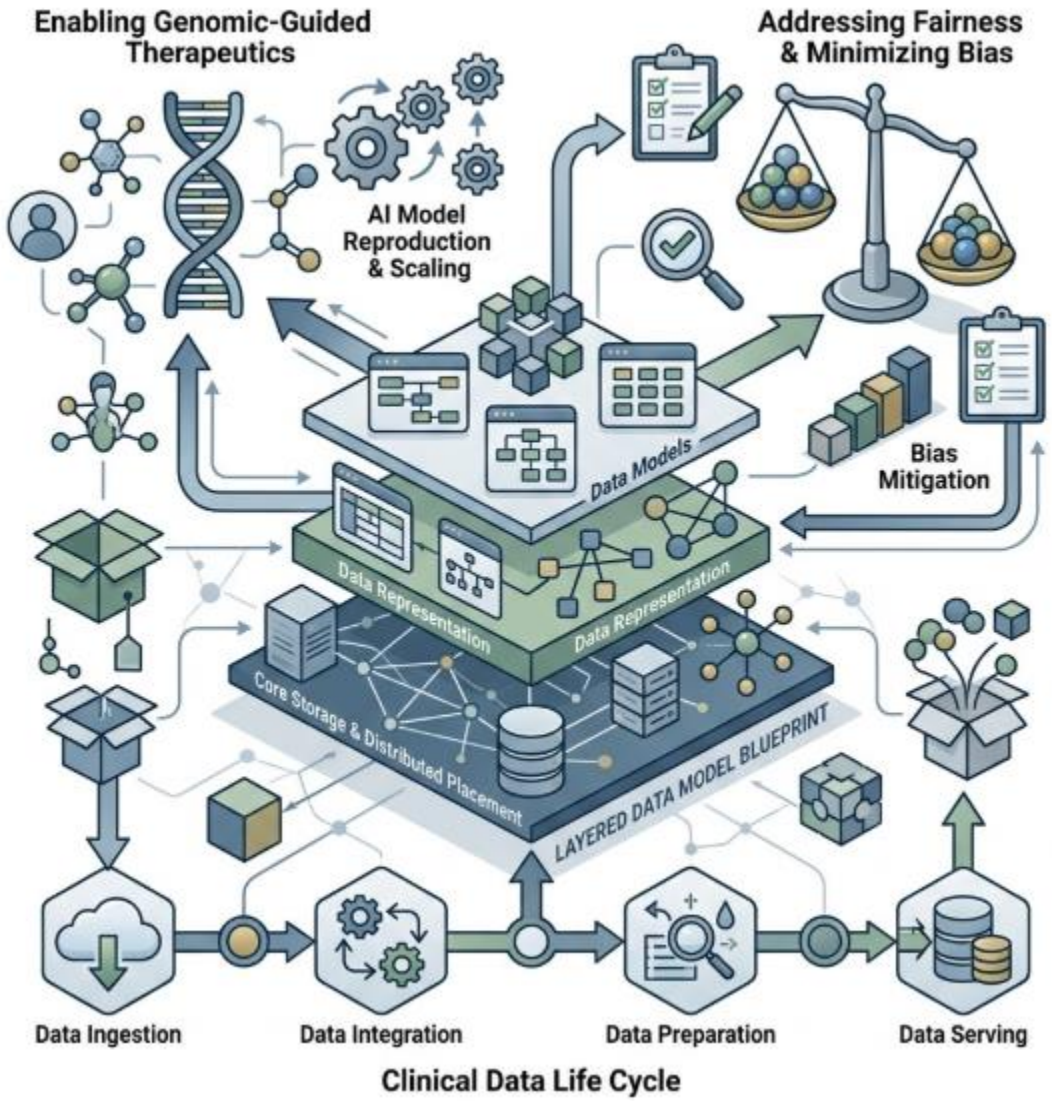

Fig 2: A Modular Data Architecture for Scalable, Fair AI in Precision Medicine and Genomic-Guided Therapeutics

4. Objectives of the Study

A comprehensive clinical data platform architecture is presented, supported by an MLOps-enabled foundation model tooling ecosystem, and demonstrated via a clinical evidence-based genomic-driven therapeutic use case, which is subsequently generalized to other AI-driven medical domains, including imaging. Data governance principles address privacy, ethical, and organizational factors. Key results identify emerging technologies and standards, propose operational metrics, and outline an adoption pathway to mitigate risk.

The proposed architecture aims to support the healthcare community's urgent and growing need for clinical data platforms structured for machine learning-based analysis and clinical translation. These platforms are anticipated to empower foundation model development, including a set of clinical analytics foundation models for structured, interpretive, supervised, and unsupervised AI-driven analysis of massive clinical data resources and clinical trial AI foundation models, enabling more efficient, cheaper, reproducible, equitable, and accurate geospatial agnostic implementation of next-generation clinical trials.

4.1. Key Study Goals and Research Questions

The principal objective of this study is to delineate the architectural foundation of Next-Generation clinical data platforms and data ecosystems. Supported by an examination of emerging technologies, standards, and use cases, the articulation of this foundation addresses three specific research questions:

1. What key architectural elements must Next-Generation clinical data platforms incorporate to sustainably support AI-driven precision medicine over the next decade?

2. Which foundational technologies and standards at present represent the most viable pathway for the realization of these architectural elements?

3. How can the clinical, translational, and population use of these underlying technologies and standards be harnessed to stimulate adoption across the increasingly diverse Next-Generation clinical informatics landscape?

5. Research Summary

The designs for next-generation clinical data platforms represent a modernization imperative, an essential architectural foundation that is characteristic of a truly data-driven

organization. Such an architecture enables a big data ecosystem capable of leveraging AI to support advanced analytics, operational decision-making, and purpose-built applications, stretching across the healthcare continuum—from the bench to the bedside and from healthcare delivery to population health.

Six foundational design principles are proposed, which facilitate a coherent architecture that supports the needs of major stakeholders in the healthcare ecosystem. These principles promote a wide breadth of real-world clinical, translational, and public health applications while optimizing for external agency concerns that can threaten the realization of an AI-driven healthcare ecosystem. The considerations identified in these principles—future granularity, provenance, interoperability, support for analytics at scale, and active data governance—are by no means exhaustive; they merely represent a minimum set that must be addressed for any substantial advancement toward AI-driven precision medicine.

5.1. Foundational Design Principles for AI-Driven Precision Medicine

Five foundational principles have emerged from the preceding analysis highlighting requirements for next-generation clinical data platforms targeted toward clinical implementation of foundation models for AI-enabled precision medicine. These principles transcend specifics of particular architectural elements and technologies and offer guidance aimed at the broader clinical community.

Data granularity, provenance, and quality. AI models are often sensitive to small perturbations in training data, motivating the creation of fine-grained knowledge bases sufficient to enable performant AI model training and validation. Such fine granularity also facilitates provenance tracking for AI, which remains an area of active research. Provenance tracking may ultimately become less important, particularly for foundation models trained at the data lake level using self-supervised or unsupervised modalities, but provenance annotation and data quality remain key requirements as AI continues to be deployed for high-stakes healthcare applications.

Interoperability and standards. AI systems are typically built using toolsets from different organizations, making data interoperability a key architectural theme. An architectural principle focused on standards, therefore, reflects clinical operational realities of information technology investments—i.e., building separable “pipes and filters” from multiple vendors—rather than a

research focus on conceiving and implementing “one-ring-to-rule-them-all” solutions. The human resources required to ensure compliance with AI-specific data standards have, until recently, been underappreciated.

6 Architectural Principles for AI-Driven Precision Medicine

The AI-driven precision medicine vision requires a next-generation clinical data fabric that is designed, organized, managed, and governed for the age of AI. Academic medical centers are embracing large-scale investments in advanced clinical, genomic, imaging, and other multi-modal information collection and storage, which provides a powerful foundation for precision medicine. Adoption must ensure that the huge collective investment produces optimal benefits by addressing four fundamental principles.

Granular, provenance-rich, structured, standardized, and machine-accessible data is the foundation for the AI transformation of precision medicine. Available data in clinical databases (electronic health records [EHRs], diagnostic testing data, treatment prescriptions, clinical notes) are selected, collated, and prepared for routine clinical use. These databases were assembled, organized, annotated, and standardized primarily for human consumption. Information technology–powered AI-based machine analysis and inference require higher levels of data quality. Data granularity refers to the level of detail in the data (fingerprint vs. spectral). Provenance captures the thorough documentation of the origin and history of data collection, generation, and preparation.

Next-generation clinical data fabric must prioritize canonical reference representations, harnessing existing ontologies where possible, and supporting new ones generated by the community. Information security, privacy protection, bias and fairness—and ultimately equity—are major global challenges associated with the consolidation and exploitation of huge volumes of data generated by many sources, modalities, and technologies.

6.1. Data Granularity and Provenance

Data granularity and provenance are key determinants of analytical capabilities. Disparate data elements stored in a temporal model support risk stratification and survival modeling, whereas a dense temporal model, with multiple observations for each patient over the study period, enables training of machine learning classifiers. Moreover, architectures that

support analytics at different spatial (regional, institutional, and national) and temporal (single time, longitudinal, and cohorts) resolutions are invaluable to address questions of varying scope.

Data provenance and annotation are critical to enable machine learning and to address model bias and the applicability of results to non-FDA datasets. Open, community-curated knowledge networks collect information using consensus approaches, such as the Gene Ontology for gene function, PubChem for small molecule–small molecule interactions, and the Cancer Genome Atlas data commons for genomic variation. Modeling languages such as the Resource Description Framework and the Web Ontology Language, and protocologies such as the Semantic Web and RDF, facilitate rich metadata annotation and provenance tracking of data objects. A growing number of federated environments, including Antares, Catena, DataChem, and the Global Alliance for Genomics and Health, leverage metadata annotations to enable quality control, drill-down inferences, and support for repurposing and contextual use of data objects by AI techniques such as transfer learning.

Automated data-labeling pipelines, capable of drawing on diverse quality-control resources such as ClinVar, facilitate the execution of von Neumann architectures on clinical data—enabling supervised machine-learning applications including genomic-guided therapeutics, redeployments of already-marketed drugs against other diseases using phenotypic mapping, identification of drug combinations and survival prediction for other diseases, and mining of imaging and radiomics databases for new diagnostic markers and therapeutic hypotheses.

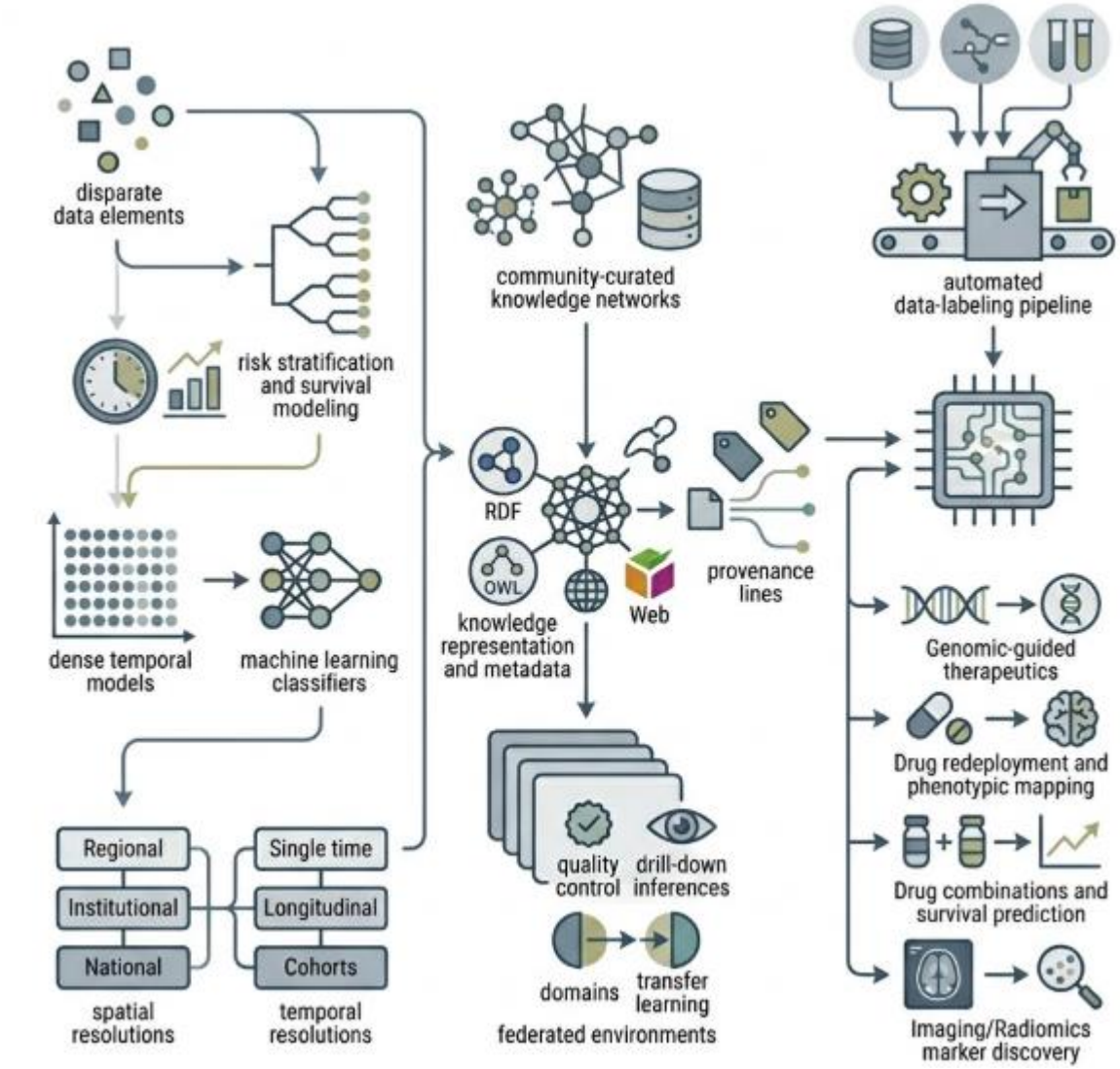

Fig 3: Granularity-Driven Machine Learning in Federated Biomedical Data Ecosystems

6.2. Interoperability and Standards

Disparate data sources and silos, lacking semantic consistency, require interoperability solutions that enable sharing among organizations. Health Level 7 (HL7) Fast Healthcare Interoperability Resources (FHIR), Common Data Model (CDM), Observational Health Data Sciences and Informatics (OHDSI)/Observational Health Data Sciences and Informatics (OHDSI)/ODHSI/ADHSI/SOHDSI/VONHDSI/VONHDSI/Independence/Independence/Independence/Independence/Independence/Independence/Independence/independencebiblisNMHI-endReliability-A-Step-KTD/?select=read&@psiz=7&@order=CREATED_DATE&@suggest=0&q=CDM&MATEINDIST=c&@indextab=Full&@submit=Submit+Request&fh=TVOBLIN&FERM=HSL1.0&FMIR=ST&OREI=WAN&NVEI=WAN&003-ND-149-OPCL&004-ND-149-OPCL-004-ND-149-OPCL&004-4&cdmodel-translational?indx=ESP&DSTR=DLPDADAB&FORMAT=Ch&PAGLIN=From&PGRCN=NHI1993&PATO=978-0-915291-68-8&RAUSHM=B&PIAF=PDGPAords&EFNCD=AI&EXPCON=GR&CDAT=2008-07-01&LSRC=PM&LDefD=El&TNTT=4&TRS=TRS-NBG&ORF=UNC&FOC=History+of+Minority+Income+Srcs+-+A-T-H+Wb&SO=2006-07-04 molemo@bdi-hub.org as a go-to state, consisting of flexible and extendable data structuresEMERGE, Enable Mental and Emotional Health to End Violent Behavior? □□□□□□□□□ □□□□□□; □□□□□□□ □□□□□ ;□□□□□□□□□□ ; □□□;□□□ Contact an Access exceptionally simple, distinctive proficient, AGI enabled, distinguished solution. These sources offer a wealth of clinical, genomic, imaging, social-economic, and behavioral data.ASDAASONG National DAASAL Boundaries of Global Scale.

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Data ingestion, storage, analytics and use must adherePrivacy by design governs the entire architecture. AI solutions formalize and augment machine intelligence with enabling technical augmentation, thus offering services and products such as image and video recognition, text translation, and complex problem solving.

7. Data Layer Architecture

The data layer transfers clinical and translational data from silos applied in other platforms, practices, or by external sponsors into a central data platform that provides an organization-wide analytics-ready environment and integrates these data for model-building/data-sharing. The data ingestion and integration component is responsible for moving and transforming the data into a proper format for the analytics platforms. This requires a considerable amount of engineering and regulatory work, particularly given the sensitive nature of the data.

The data layer architecture contains an extensive degree of flexibility and adaptability through semantic data modeling. Such modeling should be natively aligned with the Data Provenance characteristic. In Data Provenance, filtering by medical center, center level, or external sponsors allows examination of data collected, analyzed, or modeled by individual institutions and data partners while permitting consolidated data access for modeling by third parties or sponsors and sharing-usage requests to the data owners conservatively reflecting the internal provenance within the model. Hence, semantic ontology specifications and semantic data instances can be flexibly built accordingly to serve specific analysis requests.

7.1. Data Ingestion and Integration

Data ingestion and integration comprise the first critical subcomponent of the data layer architecture, designed to support AI foundations for precision medicine. These elements consider the machine learning lifecycle—from data preparation through model training and deployment—and the deconstruction of downstream processes in the clinical and translational domains into detect-and-treat modules. Initial attention focuses on the I in AI, particularly the volume, variety, velocity, and veracity of data and how they impact machine learning. Model preparatory tasks

include preprocessing, cleansing, transformation, and consolidation, all of which are cataloged, discovered, versioned, orchestrated, and validated. Seven spatial-temporal considerations for inclusion are spatial and temporal labeling, spatial and temporal span, spatial proximity, proximity reference, temporality association, temporal relations, and temporal associations.

Collectively, provenance and model preparatory tasks form the input for AI foundation models and accelerate detect-and-treat readiness via an AIOps approach. Normally associated with MLOps, the operations management of AI foundation models also encompasses the consideration and modeling of bias, fairness, and privacy. Machine learning—particularly supervised learning—heavily depends on detailed, high-fidelity labels. The extent to which labelers influence detection and treatment directly affects fairness and bias. In parallel, rapid advances in large models expose the limitations of niche expert models and change the playbook for quality assurance in machine learning. Capability shortages in supervised label availability and quality provide an opportunity for foundation models to be framed for utilization at scale and engender an alternative AIOps strategy, namely, the exploration of foundation model release notes for synthetic use cases.

7.2. Data Modeling and Ontologies

Effective data modeling that enforces minimum granularity requirements provides a powerful mechanism for ensuring data capture with significance and utility for clinical and translational research. A preference for models grounded in domain-specific ontologies supports population-scaled predictive modeling, with the selection of a particular ontology guided by federated data-search considerations.

AI-driven precision medicine leverages vast amounts of clinical, imaging, wearable, and other human-generated data, retrieved from a variety of clinical and research sources, and combined with vast other nonhuman-generated data—building a wealth of petabytes of data and population-scaled AI foundation models. These foundation models for AI-powered precision medicine can directly leverage the power of re-training, where a large foundation model is adjusted for further prediction tasks by scaling the training dataset with smaller additional datasets. Ontologies, built on the principles of treating the concepts of the domain of discourse as a directed labeled graph, focus on expressing the semantics, interrelationships, and meaning of the concepts of a domain rather than on the concepts themselves. In the context of building ontologies for AI-powered precision medicine, the idea is therefore to develop domain-specific

concepts that can offer optimum value for AI-based training for true generalization, as expressed by the concepts of bias-variance trade-off in supervised learning.

Population-scaled predictive modeling provides naturally supportive bias-variance trade-offs. Population-scaled predictive analysis considers the whole population of data-points from multiple sources rather than a single task-target training dataset, thus utilizing the cross-task commonality of multiple training labels to provide naturally aggregated dataset signals for training an AI model for a particular task. The very size of the complete dataset makes it possible to undertake latent-space learning with a single-task training label, because the learning points in the other tasks can be treated as independent variables. Thus, for a large-scale imaging prediction task, an AI skilled at identifying wrist fracture on X-ray images may not possess necessarily superior predictive ability compared to an AI skilled at segregating metallic objects in wrist images. Therefore, the choice of ontology that serves the optimal predictive modeling for a federated data-search operating on the AI-driven precision medicine data-platform becomes crucial for its analytical applicability.

8. Analytics Layer for AI

The architecture provides a foundation for the analytics layer catering to diverse clinical and translational use cases requiring different forms of AI, ranging from descriptive and exploratory analytics to foundation models and generative AI. Clinical applications such as genomic-guided therapeutics or radiomics-driven medical image analysis can benefit from training specific machine learning models. Family of domain-specific foundation models need to be built for specific (biomedical, clinical or public health) domains to achieve the full potential of generative AI, whilst also adopting end-to-end generative AI approaches that embrace all modalities in the same model. A comprehensive Machine Learning Lifecycle Management and MLOps framework is required to manage the end-to-end machine learning lifecycle across training, serving and observing models in production.

A data architecture for AI-powered precision medicine cannot be complete without careful consideration of the analytics-layer capabilities and tooling that are required to serve the myriad clinical and translational use cases “on the other side” of the data and AI platforms. For example, platform capabilities need to extend beyond data management support for genomic-guided therapeutic decision support systems in the domain of precision oncology. Indeed, these capabilities are manifested in the recent explosion of medical foundation models for loci, drugs,

diseases, proteins etc., complete end-to-end multimodal models of imaging, medical report and electronic health record information, or the emerging family of models for simulating data directly.

8.1. Foundation Models and Tooling

In recent years, pre-trained transformer-based models have demonstrated remarkable generalization and transfer learning capabilities across diverse application domains. Recent advancements, such as GPT-2, GPT-3, LaMDA, and DALL-E, have set new benchmarks in Natural Language Processing (NLP), text-image multi-modality, and text-generation quality. In NLP, highly effective foundation models can be created across complex tasks by taking advantage of large pre-trained models and fine-tuning them on task-specific data. Great strides have also been made in foundation-model-aware training paradigms, such as visual grounding and text-to-image generation, as well as in the development of new model architectures, such as CLIP.

In addition to NLP, foundation-model-like approaches are gaining traction for structured-data machine-learning applications, with recent work showing that more extensive, appropriately distributed datasets lead to better model generalization. As highlighted by research in intent detection, automated trend prediction, and earthquake prediction, clustering repositories of historical-provenance-documented structured data can yield result-determining features for many applications. These findings indicate that a similar foundation-model-like approach could be applied to predictive analytics on augmented PROTECTED-Subject data and for clinical annotation of non-PROTECTED visual data. Moreover, the ML Toolbox extension of PaloAlto.AI provides consolidated, low-latency, and cost-optimized pipelines for geotechnical data analysis on multi-gigabyte structured datasets.

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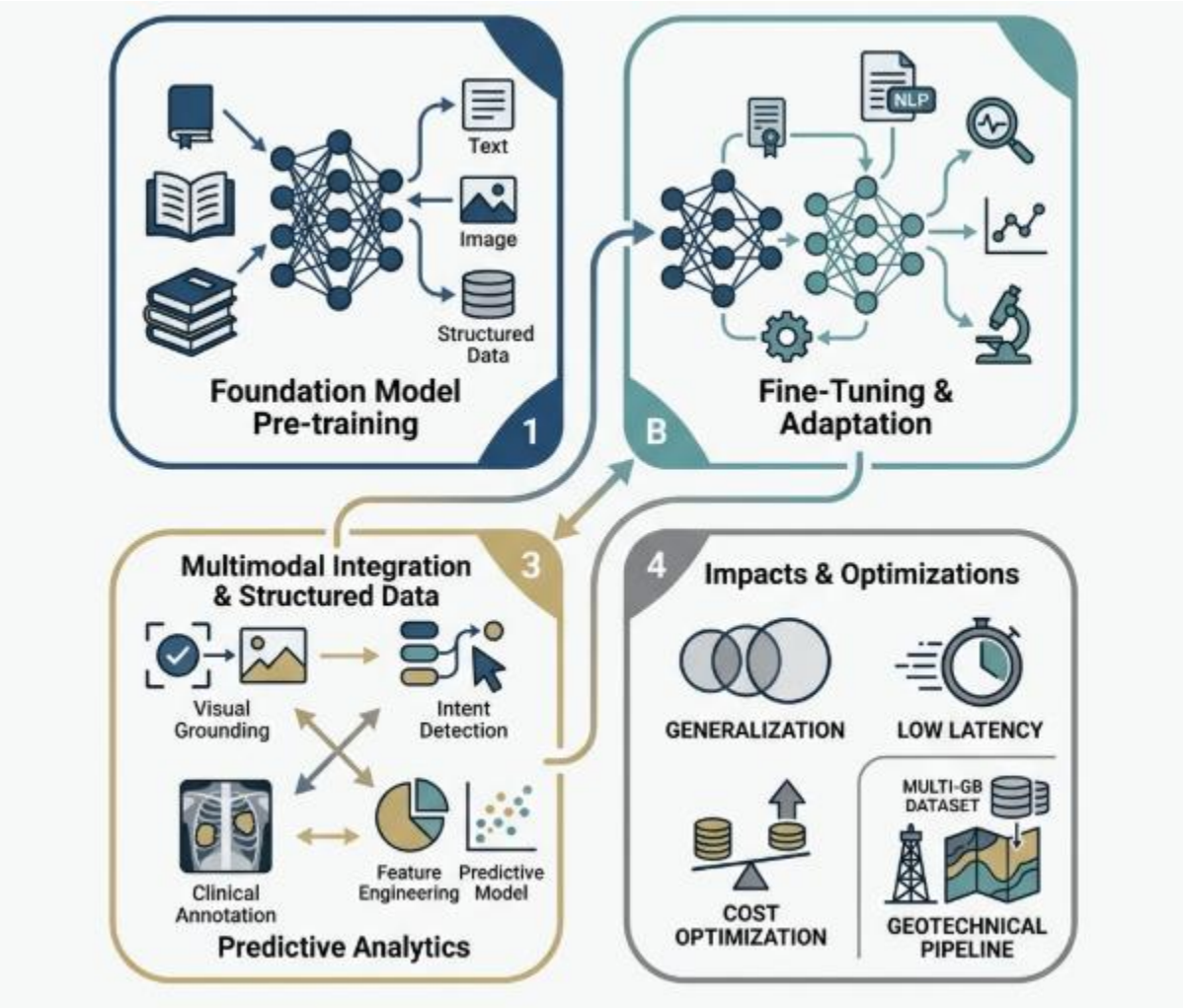

Fig 4: Cross-Domain Generalization in Foundation Models: Systemic Applications in Natural Language, Multimodal Learning, and Optimized Structured Data Analytics

8.2. Machine Learning Lifecycle and MLOps

Structured Machine Learning Operations (MLOps) address the Machine Learning Lifecycle and its five phases (inspired by Google's MLOps framework). These are: (1) Creation,

which gathers data, prepares it, and builds and evaluates models; (2) Deployment, the production version of the model becomes available for scoring; (3) Monitoring, the model is monitored for changes; (4) Operations, operational data flows in real time through the production model; and (5) Governance, a control plane ensures platform policies and operating procedures are being followed.

Machine Learning Operations (MLOps) are the application of DevOps-like processes and tooling to machine learning projects. The nature of machine learning differs enough from traditional software development that specific roles, phases, tools, and techniques can be defined. Actual implementations build on these ideas, but often also create terms and concepts not considered here. The data scientists building the models rely on the rest of IT for availability, security, redundancy, and performance and can treat the scoring service as a black box, known only by service-level agreement. The Data Engineering services are structured like the core components of a typical data pipeline/warehouse: ingest with data cleansing and enrichment; an offline pipeline that supports wider access and enables training; a model training, evaluation, and scoring strategy; and, finally, an online pipeline that sends data in real time for scoring.

9. Clinical and Translational Use Cases

AI-driven precision medicine has the potential to benefit a broad range of clinical applications within the domain of learning healthcare systems, spanning internal medicine and cardiology to advanced neurological care. However, clinical success will require an effective balance of automation, empowerment, and practical clinical integration, thus creating adequate human-in-the-loop mechanisms with patients and healthcare practitioners at all stages of high-stakes decision making.

Arguably, the most mature area of clinical application lies in genomic-guided therapeutic interventions for precision oncology and, more recently, precision treatment strategies for inflammatory bowel disease. Next-generation sequencing technologies generate comprehensive genomic profiles for many cancer patients, enabling a rapidly growing list of targetable alterations with rationally designed therapeutics. Accurate interpretation of variant functional impact and identification of patient-specific biospecimens remain ongoing challenges. Advanced radiomic-based evaluation of tumor response to therapy may further enhance outcomes and reduce toxicities. The implementation of clinical trial-in-the-loop systems can facilitate patient stratification for ongoing and future clinical trials of experimental therapeutics.

9.1. Genomic-Guided Therapeutics

Genomic sequencing initiatives are rapidly producing huge volumes of high-resolution genomic data for patients affected by cancer and many other diseases. Currently, most of this data is underutilized because the required expertise to interpret it is limited to only a small number of organizations. Advances in natural language processing (NLP), especially with large language models (LLMs), provide an opportunity to enable even non-experts to harness recent discoveries contained in the biomedical literature and rapidly capture genomic variants that were previously neglected due to the manual effort required. This is particularly relevant for rare diseases, where personalizing a treatment depends on identifying the best possible solution from a set of very few or even just one similar previous case.

Another constraint that LLMs can help mitigate is the availability of curated datasets for training. Large generative foundation models, such as those used in BigScience and Bloom, have shown that directly-training a large language model from scratch results in significantly worse performance than a standard transfer learning approach. Despite being relatively big temporal and financial undertakings, these projects have demonstrated that sharing expertise, data, and computing resources among a broad number of collaborators produces state-of-the-art results. They have also shown that biomedical foundation models can be trained directly from scratch in a matter of weeks, and that performance strongly improves when specific-domain data is fine-tuned onto smaller models. The goal is to use these recent advances in foundation-model-based NLP to democratize genomic-guided therapeutics for rare diseases, particularly for histiocytosis, through an easily-usable web interface.

9.2. Imaging and Radiomics

Until recently, images such as X-rays, MRIs, and CT scans have offered limited support for precision medicine. However, increasing attention is now being paid to radiomics, a field at the intersection of computer vision and radiology. By converting medical imaging data into mineable, high-dimensional feature information for each patient, radiomics aims to facilitate diagnosis, prediction of prognosis, and response to treatment. Data-driven radiomics approaches have shown remarkable promise in addressing key challenges in oncology, including early detection, prevention, and individualized treatment. These methods utilize radiomic signatures extracted from pre-therapy images of the primary tumor to predict incomplete response and early recurrence after treatment in multiple cancers. Such signatures can also serve as prognostic

markers. Machine learning approaches capable of lifelong learning are now emerging and will be crucial for developing truly intelligent and robust medical imaging.

Recognizing this, the still largely unexplored area of radiomics has been named the "new frontier" in precision medicine by prominent researchers. The field is expected to enter the deep-learning era soon, with deep learning already yielding impressive advances, including integrated segmentation-classification networks for CT images and automatic detection-and-qualification systems for the chest. It has been suggested that radiomics can be applied to all cancers and that breeding more robust models for multisource imagings will help drive the next step of radiomics as the "radiogenomics" era. Moreover, the very dynamic development of AI in the imaging field suggests that research and applications should be extended in several directions, including economic effects, academic and industry linkage, exploratory ward rounds, and educational systems. Remembering that deep-learning methods require a large volume of representative data, it is hoped that sharing radiomic data by various centers will facilitate further exploration of the enormous potential of this booming field.

10. Data Governance and Ethics

Due to their nature, clinical data platforms encounter a closer scrutiny on data privacy, security, and ethics compared to generic Big Data Platforms. The collection, storage, and use of patient data is subject to various regulations and laws, such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR). These regulations promote standards and technologies that address the ethical risks that arise from bias, fairness, and equity.

A clinical data platform–approach for AI/ML-enabled data science and decision support in healthcare assures secure management of sensitive health data in terms of compliance with privacy regulations. Moreover, according to the new privacy-by-design paradigm, privacy is not added on afterward but is built in at every stage. Consequently, there appears to be little overhead, cost, or inconvenience to using an AI/ML-enabled data science service for predictive analytics and decision support. The foundation-modeling technique makes it possible to learn from combined knowledge of many diverse, institutionally limited, and sensitive datasets while preserving patient privacy. Distinct patient populations may have quite different disease manifestations.

10.1. Privacy Preservation Techniques

Back-End Support for User-Controlled Privacy Preservation

Techniques supporting search and analytics on distributed and federated data without requiring sharing of identifiers—among them Secure Multi-Party Computation (SMPC), Homomorphic Encryption, Differential Privacy (DP), Private Information Retrieval, Zero-Knowledge Proofs, Ordnance Signatures, and Fully Homomorphic Encryption (FHE)—energy the quest for privacy-preserving methods. Each has strengths and weaknesses evident in applications such as Distributed Pivoting. SMPC has been used successfully in multiple cloud confederation schemes supporting analytics against jointly held data without party violating Data use agreements or being burdened with tracking user consent for (de-identified) secondary data use.

Genetic analysis poses a very different site for privacy-preserving search. The data-use agreements underpinning genome data often restrict even subsetting. The main stream defense against misuse by, say, a class of users having different power profiles, is differential privacy, which adds random noise to the s-promises, receive-queries-and-answers model. DP possesses a projection property that allows answer queries on subset data without invalidation. Counteracting the weakness of non-monotonicity under local-DP is achieved via server-side techniques.

Private-Information-Retrieval (PIR) protects the user from revealing either the content of her query or the index to which she is requesting the associated answer. Certain PIR schemes, along with Zero-Knowledge Proofs, allow queries without revealing identities. Secure Database systems utilize both tools to enable unencrypted query-runs on sensitive data.

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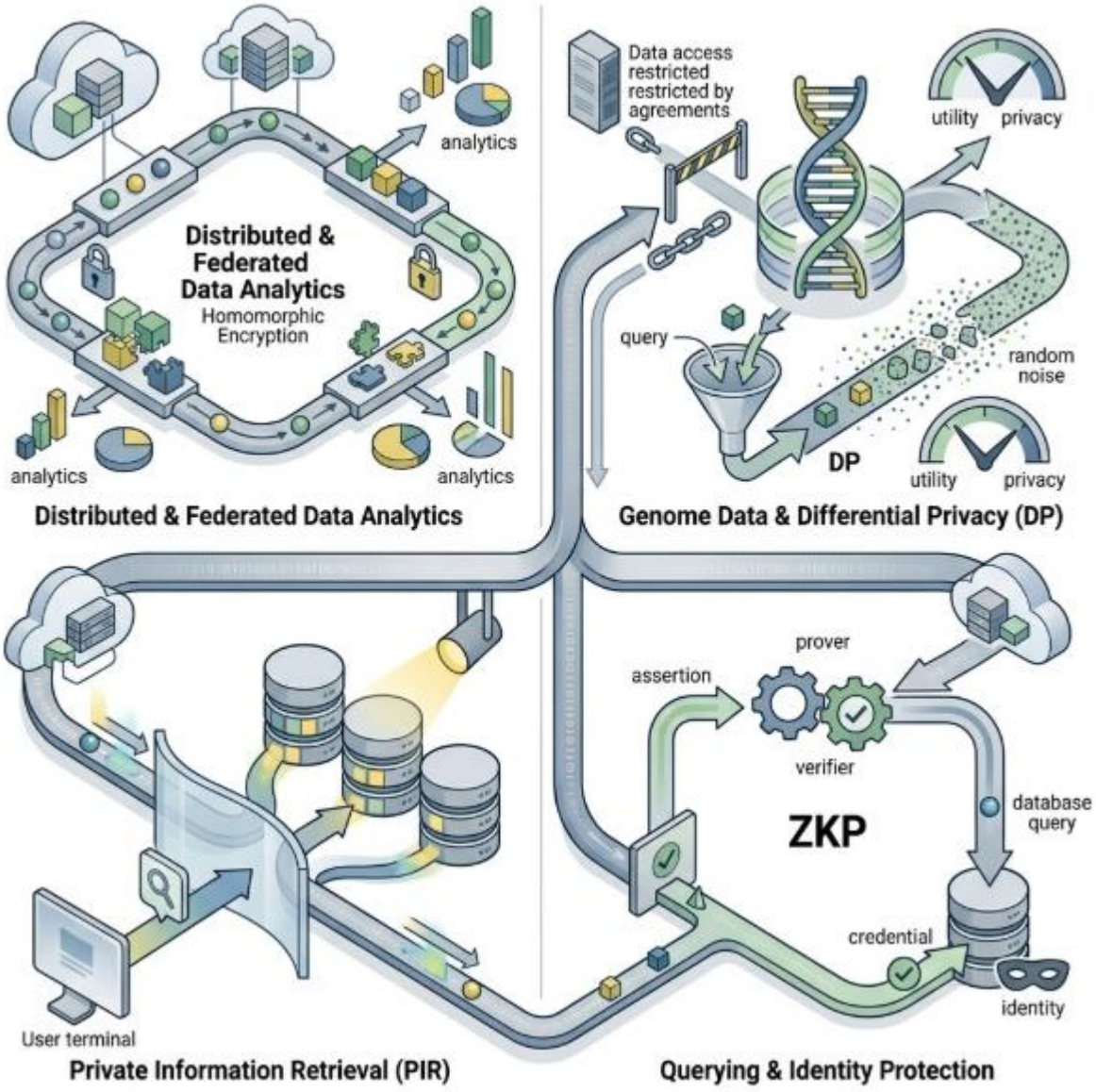

Fig 5: Architectural Synergies in Federated Privacy: Orchestrating SMPC, Differential Privacy, and PIR for Secure Distributed Analytics

10.2. Bias, Fairness, and Equity

A core mandate of Next-Generation Clinical Data Platforms is helping eliminate bias in AI-derived decision-making in medicine. The elimination of bias is critical, especially in widely used screening algorithms, such as those used in radiology, cardiology, urology, and surgery. Methods for modeling and mitigating bias, fairness, and equity in AI-driven systems generally remain poorly understood. Popular group fairness metrics can mask inequities by necessitating only an overall balance in model predictions across groups, rather than requiring such balance for different slices of the data. Indeed, group fairness can lead to poor outcomes for subgroups that are not well represented in the data used for training. Although the lack of fairness-aware predictors in clinical applications is not a key methodological gap in the literature, the need for such predictors seems substantial given the ultimate goal of decision-making in medicine: improving individual patient outcomes. Unfair systems can degrade algorithmic performance within sensitive subgroups. Furthermore, it might finally be possible to examine complex trade-offs between performance and fairness in clinical applications.

Bias is often generated by the use of poorly representative datasets. Although protocol-directed data acquisition during clinical care is designed to provide clinically useful generalizable solutions, such acquisitions still require subsequent annotation by expert panels in a validated multi-level consensus-driven model. Next-Generation Clinical Data Platforms can include bias detection and correction tools. One potential avenue is the combination of decomposition techniques with re-weighting—principally the use of Adversarially-Reweighed Classification to combine two commonly used approaches in the literature: preprocessing and in-processing.

11. Implementation Challenges and Risk Mitigation

Data platforms for AI-powered precision medicine will be prone to several implementation challenges. Interoperability constraints among decision-support platforms represent an entry barrier. Therefore, implementation cost, risk, and usability will benefit from focusing the initial effort on a single ontologically founded platform. Yet, the effectiveness of AI decision-support relies not only on data quality and quantity but also on user uptake. Addressing change management, including motivating clinicians to retrain and acquire new skills required to integrate ML into decision-making, will help overcome this obstacle.

Out-of-the-box ML might exacerbate bias and equity disparities in clinical outcome predictions, diagnosis, or treatment. Accordingly, AI impact monitoring should become routine and include a demographic lens. Deploying AI responsibly and equitably requires engaged communities, fairness-aware risk assessment, continual human oversight, diverse and representative training data, supportive tech, and collaboration across sectors. Awareness and training are prerequisites for user uptake of ML tools that improve clinical outcomes, reduce costs, and lower caregiver burnout but do not yet have robust scientific validation.

11.1. Interoperability Constraints

Interoperability is fundamental to making data discoverable and usable. The growing descriptions of the data-hub ecosystem have focused on defining the processes of collaboration and governance. But these efforts have not yet converged to concrete interoperability specifications at all levels of the IHE framework for clinical data hubs. While the information model for core clinical data shares is defined, the architectural requirements and processes of synthesis are lacking. The failure of terminologies (primarily RadLex, SNOMED, and LOINC) for standardized model creation, including imaging and genomic domains, concurs. The depth of clinical detail and integration supported by the environment will be dependent on a cross-institution cooperative approach to bioinformatics—model creation through unification; concurrent environments that jointly curate data and metadata; and the completion of a central resource that normalizes and publishes newly detected relationships.

Life Science domains need to broaden the use of the Biomedical Research Integrated Domain Ontology and Machine-readable and RESTful web services (BioPortal, Open Biomedical Ontologies, and Bioconnector) to encourage single-instance distributions that facilitate meta-integration and are annotation ready for primary analysis and pre-publication sharing. The model is introducing the concept of a meta-annotation hub to research data (the Bioconductor MAnD network) and extending the BioSharing Directory to service LabArchives-like services. AI offers unprecedented opportunities to study and explore the unifying principles of disease, biology, and development by modeling hundreds of millions of datasets, but challenges remain. Training data-convergent medical concepts in natural language on Internet-scale corpora is not sufficient for next-generation systems, because domain knowledge constrains the efficiency and quality with which neural nets transport knowledge representation and processing.

11.2. Organizational Change Management

An organization-wide cultural shift is necessary to expand the accessibility of clinical data and advance its responsible usage. Change management strategies should acknowledge, support, and facilitate the necessary behavioral changes, working to create a supportive environment. Adoption pathways for framework elements should be developed based on stakeholder engagement and cooperation.

Organizational change management, emphasizing empathy with stakeholders, can address anticipated resistance to data sharing. Leadership attention and commitment are essential for success in both external partnerships and internal transformation. An approach that encourages bottom-up participation and allows people to participate in, contribute to, and experience transformation favors both adoption processes and overarching corporate strategy.

12. Results

Results indicate several key components of next-generation clinical data platforms: (1) Genomic and clinical data sources fundamental to the emergence of integrated foundation models for human health, and (2) Privacy-preserving data-sharing and community-engaged data-collection strategies along with mechanisms to ensure that model predictions support healthcare equity. Results also identify technical solutions and adoption paths for positive risk management at scale in the context of AI-guided precision medicine.

An important signal is the first working version of a minimal AI foundation model for human health based on a symbiotic combination of textual health information and genomic data curated using an open-source toolkit implementing the emerging Health Level 7 Fast Healthcare Interoperability Resources standard. Predictive systems created using the model are designed to bridge centre-based machine learning capability gaps to support organizations-in-variance through their adoption of responsible AI, while mitigating the risk of deploying such predictions.

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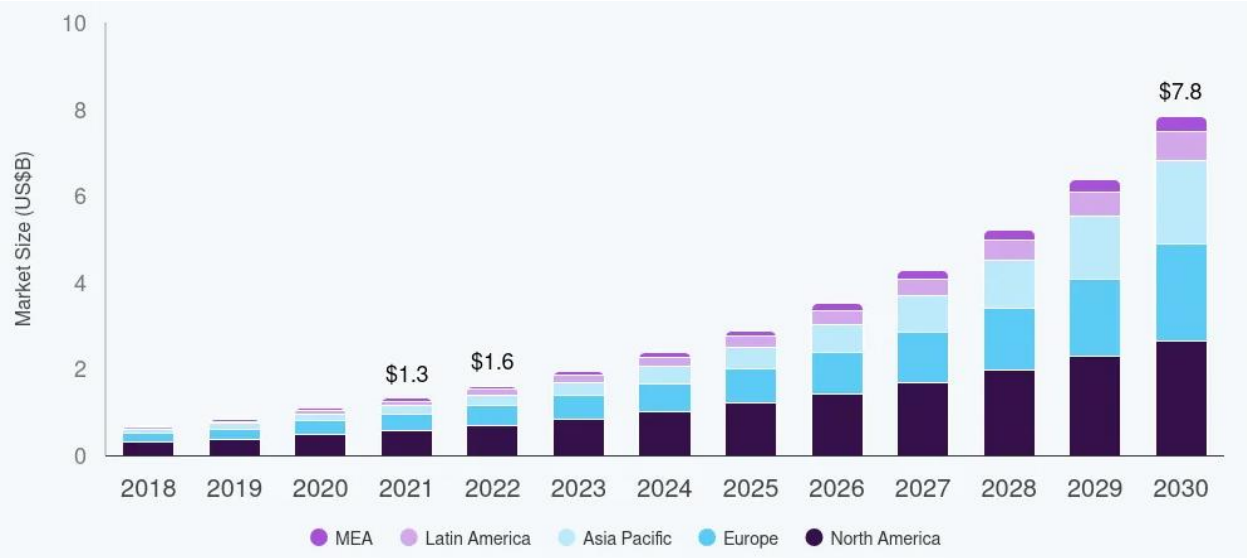

Fig 6: AI-based Clinical Trials Solution Provider Market Report 2030

12.1. Emerging Technologies and Standards

The advent of AI and large-scale clinical data has laid the foundation for transformative technologies within NCDPs. Among these are foundation models (e.g., generative models, large language models) that leverage extensive datasets from sources such as the Internet and GitHub. In addition to enabling novel AI applications, these foundation models serve as universal predictors for various data types and support new paradigms within AI, including prompt engineering, self-supervised learning, in-context learning, and few-shot and one-shot learning. Open-source foundation models and specialized tooling further empower biomedical research and development. Productization of these capabilities will simplify the task of building next-generation enterprise ML and AI systems.

Over the next decade, some features of NCDPs will become standardized and widely adopted across organizations, thereby enhancing overall ecosystem value. Emerging technologies, frameworks, and standards will be key enablers of this shift, and several are already gaining traction. The HL7 FHIR framework is moving beyond limited deployment primarily by technology vendors toward broader adoption across multiple sectors, especially by

healthcare insurers, biopharma, and healthcare providers. Cloud-based MLOps tooling is rapidly maturing, facilitating greater adoption of reproducible ML and AI system deployments aligned with best practices. Privacy-preserving machine learning is reaching technology maturity and being systematically evaluated for incorporation into emerging standards."

12.2. Adoption Pathways and Metrics

Advancing AI-driven precision medicine requires not only data platform redesign, but also addressing broader factors that have previously delayed or derailed such initiatives. Two surveys of opinion leaders in data science, AI, and precision medicine suggest that four distinct paths are critical. First, the adoption of revolutionary new technologies and new standards across the AI landscape—including the mechanics of large foundation models, the use of multimodal learning to unite different types of data, the tools and techniques for neural-symbolic learning, and techniques and protocols for tokenization—should speed and improve disease diagnosis and reduce detection and response times for epidemics and pandemics. AI growth paths and industry imperatives are also transforming business models across diverse sectors. Second, the establishment of open-access digital twins of humans and human pathology will enable more appropriate and inclusive clinical trials, larger patient cohorts across rare diseases, integration of more-mature preclinical models, and improvements in the interpretability and transferability of AI products.

Third, patient advocates and community organizations manage the implications of AI for health equity and health equity. Stakeholder identification and engagement should be evaluated across the lifecycle of all relevant projects and all AI products and services. Structured methodologies for stakeholder engagement are now standard in business, technology, and corporate social responsibility. Finally, the proactive identification of technical and clinical areas of interest to committed funders should also accelerate the rollout of AI for AI-driven precision medicine. Focusing on a small number of technologies and their strategic application across Precision Medicine on an Principles for Implementation Pathways Causal Agent Matrix (opposite) is an effective and well-established approach in science, business, and investment.

13. Conclusion

The proposed principles provide valuable guidance for organizations pursuing precision medicine and precision health. Unlike many emerging technologies, they outline an evolutionary

pathway that embraces existing federated and centralized models while establishing an evidence-based, comprehensive data architecture for next-generation clinical data platforms. Such platforms should go beyond traditional clinical data warehouses and be recognized as large-scale, full-lifecycle, clinical data management systems that directly enable research, AI, and analytics. The domain-savvy community must now cultivate these platforms and their associated AI systems like large-scale digital gardens with rapid iterations, regular weeding, and continual progress. Helping these systems flourish will pave the way for the rapid deployment of safe, trustworthy, AI-enabled genomic-guided therapies that intelligently honor the spirit of the Hippocratic oath.

The vision delivery requires large-scale AI foundations that can integrate large-scale data and analytical capabilities over data and geographies. Specifically, the pathway for aNational Clinical Data Floor™ (NCDF), a Commonwealth Clinical Data Platform (CCDP) program in Australia, and federated security and governance-enabled open-source collaborative efforts must also consider the AI foundations. The National-AI Roadmap highlights potentials, challenges, and an anticipatory impact-oriented complete-data infrastructure that can be used for the AI-enabled near real-time Pharmaceutical Project. Even in disrupted circumstances, such as the COVID-19 pandemic, continued allocation toward these foundations must be sustained to enable the prized uses of intelligence at scale for the common good.

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