



Linking Providers and Payers for Better Care

Tanja Schultz
Asst Professor

Abstract

The recent COVID-19 pandemic has emphasized the need for resilience in health service delivery. One avenue to support resilience is through an integrated clinical-payer intelligence infrastructure that leverages all data generated from routine clinical practice and operations, not just for service reimbursement or regulatory compliance, but also for real-time service delivery decision support. Current health data usability is limited by barriers in interoperability, privacy, security, clinical validity, and governance. Addressing these barriers through a unified intelligence fabric—encompassing data commons, analytics pipelines, dashboards, and predictive models that span both clinical and payer data—could enhance the resilience of not only individual health systems but also geographically dispersed systems serving the same population.

The continuity of care and quality of clinical outcomes in any health system can deteriorate during unexpected events (e.g., COVID-19, hurricanes, wildfires) that divert resources away from routine functions or when natural disasters severely disrupt the normal operation of health services. A unified clinical-payer intelligence fabric designed to address these challenges has the potential to simulate outcome scenarios for unplanned disruptions and identify clinical conditions or care pathways requiring expedited planning or resource allocation. Transitioning from government-mandated plans (layout of service delivery–insurance claims coordination) to formalized CIA—network-enabled shared responsibility—is also critical for real-time patient, institutional, and payer collaboration to ensure the completion of proposed care orders along the approved pathway, improving service delivery quality at lower cost.

Keywords :Health services research, data integration, clinical intersections, funding intersections, clinical care disruptions, anticipated demand, exploratory modelling, deployment readiness, sentinel indicators, learnings and corrective actions.

1. Introduction

Resilient delivery of health services relies on an integrated intelligence fabric linking clinical and payer data at scale. Interoperability gaps in these external data streams hinder the precision of analysis and real-time decision making. Using a unified intelligence architecture, linking structures are added to clinical datasets to enable privacy-preserving information exchange with payers. Such an ecosystem can provide relevant signals that enhance the continuity, coordination, and safety of care provisioning even during local or global disruptions.

It is now widely recognized that health service delivery must be resilient during disruption — either during local bursts of demand for health services or service outages, or during larger global interruptions. Disruption-resilient service delivery requires the integration of an array of clinical and non-clinical resources available for patient care, and requires easy access to critical insights by the decision makers overseeing service delivery. Real-time availability of such consolidated insights at multiple granularities is feasible only when the data sources feeding the decision support are themselves reliable, accurate, and undergo preparation to serve the target use case. In the case of the COVID-19 pandemic, the use of an intelligence solution was limited by the ad-hoc integration of external data signals — chiefly related to surges, resource availability, and



approved pathways for care. Interoperability gaps between clinical datasets and such external sources of information added noise to the analysis and hindered timely decision making.



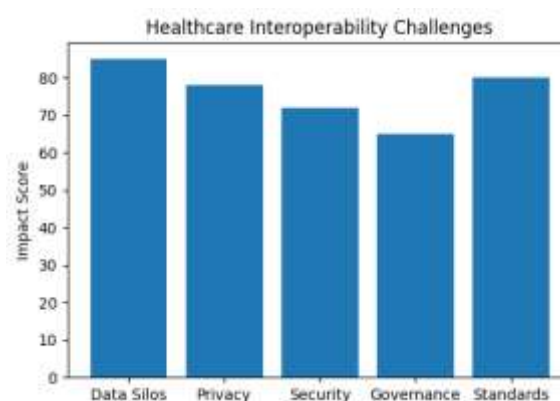
Fig 1: Unified Clinical-Payer Intelligence Fabric for Resilient Health

1.1. Interoperability barriers

Heterogeneity and lack of interoperability create silos in clinical and payer data and hinder advanced descriptive, predictive, prescriptive, and causal analytical capabilities across both ecosystem domains. Advanced analytics on integrated clinical-payer data are mutually beneficial—clinical signals generate novel reimbursement pathways, in addition to coding denials; real-time reimbursement signals mitigate contract violations and unscrupulous billing practices; payer data and models illuminate clinical management strategies; requirements of continuous contractual compliance drive operational improvements on both sides. However, competition and privacy concerns make data sharing reluctant.

Technology tools now make it possible to overcome the aforementioned barriers economically and securely. Data lakes enable storage of all clinical-payer data in raw format, scaling horizontally to accommodate heterogeneous data types; semantic harmonization layers bring together like items across data sources, alleviating de-silo-ing efforts at query time; advanced descriptive analytics generate dashboards that integrate clinical-payer data with external signals; and scale-out distributed computing frameworks simplify execution of

complex workflows. Holistic clinical-payer Causal analysis enables evaluation of change-focused interventions (e.g., care pathways) on service efficiency and clinical outcomes.



1.2. privacy, security, and trust

Fostering trust and trustworthiness is paramount for a unified clinical-payer intelligence fabric that brings together private and sensitive data from multiple stakeholders in a shared infrastructure. Gaining deep trust from the various stakeholders requires transparent and effective governance, complemented by strong technical solutions aimed at achieving appropriate levels of privacy, security, confidentiality, and data protection—certified through independent audits and verifications—for sensitive data.

Privacy-preserving mechanisms, such as fully homomorphic encryption, secure multi-party computation, and trusted execution environments, offer exciting new possibilities for designing data infrastructures and analytics pipelines that operate without ever having direct access to sensitive data. Such solutions, still mainly in the research stage, must be evaluated, matured, and deployed for use cases where users and third parties don't have a trusted relationship, typically involving sensitive data. Employing a trusted third party that gains the capability to re-identify users or that is subjected to regulation and oversight, or relying on other solutions with lower degrees of trust, makes the analytics process more



acceptable. Nevertheless, the critical requirement of designing solutions that protect privacy while enabling data to be useful remains an open challenge.

Table 1. Key Challenges and Proposed Solutions in Unified Clinical-Payer Intelligence Fabric

Challenge Area	Identified Problem	Proposed Solution	Expected Outcome
Interoperability	Fragmented clinical and payer systems	Semantic harmonization and interoperable data standards	Unified analytics and coordinated care
Privacy & Security	Sensitive patient and payer information risks	Homomorphic encryption, secure computation, governance frameworks	Secure data sharing and trust
Clinical Validity	Inconsistent predictive accuracy	Clinical Resilience Validity Index and multi-item validation scales	Reliable decision support
Governance	Conflicting stakeholder priorities	Independent AI governance board	Shared accountability and transparency
Scalability	Increasing data volume and complexity	Distributed cloud-edge infrastructure	High availability and resilience
Care Coordination	Disconnected workflows during crises	Real-time clinical-payer	Improved continuity of care

Challenge Area Identified Problem Proposed Solution Expected Outcome

intelligence
pathways

1.3. clinical validity and governance

A multi-item scale allows an index summary to be derived from a research study yielding clinically valid and practically meaningful model-based solutions and insights. Fitting a multivariate normal distribution to a set of clinical-level predictive models using real-world data enables a summary index to be derived for health service continuity when supported by a range of health service resilience factors. Conversely, the absence of supporting resilience factors causes actual continuity of care to deviate from the prediction. The resulting Clinical Resilience Validity Index, thus created and validated, can be used to highlight mismatches between the predictive and actual continuity of care during periods of disruption.

Health service continuity remains a critical priority for health systems during emergencies such as the COVID-19 pandemic. Scant evidence, however, exists at the health service level on the conditions underpinning the likelihood of continuity of care during periods of resource constraint and surges in demand. An evaluation framework is needed to identify conditions arising from shrinkage in service delivery capability that might compromise continuity of care. A set of resilience enabling factors and their relationship with health service continuity of care during the pandemic are examined. A multi-item scale allows an index summary to be derived from a research study yielding clinically valid and practically meaningful model-based solutions and insights.

Equation 1: Clinical Resilience Validity Index (CRVI)

The paper discusses a *Clinical Resilience Validity Index* for measuring continuity of care during disruptions.



$$CRVI = \sum_{i=1}^n w_i R_i$$

Where:

- R_i = resilience factor score
- w_i = weight of resilience factor
- n = total resilience indicators

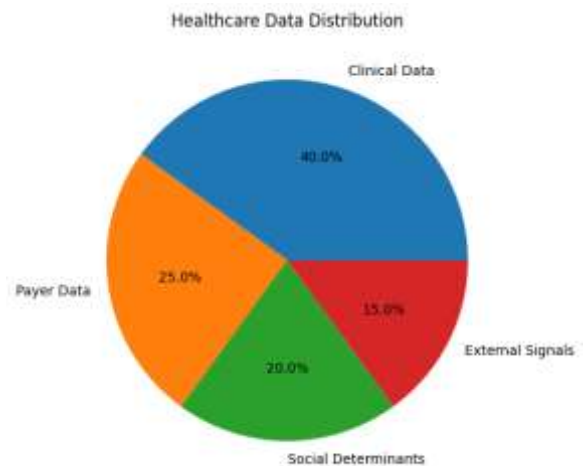
2. Conceptual Foundations

A clinical-payer intelligence ecosystem integrates clinical networks and payer data to inform population health management and monitor the service provision continuity. Point addresses the business justification and participating entities.

Data models operating under a shared vision of health serve the community that depends on them while allowing aggregate insights for different use cases. Nevertheless, data-sharing models usually belong to disparate business domains, supported by diverse incentives that compete rather than complement. In health care, providers operate within restricted budgets while trying to deliver high-quality services. Add the usage of service delivery for monetary gains in its market form, and information becomes asymmetric. Addressing this concern, an integrated clinical-payer intelligence ecosystem provides a shared resource for resilience in health service delivery.

Complementing existing models for continuity of care, a clinical-payer intelligence fabric provides a shared resource for resilience in health care service delivery. Such ecosystems integrate clinical networks with payer data from health insurers, public health authorities, and third-party payers. Merging data dedicated to reimbursement with those that describe the conditions of patients and providers enables analysis of the population status, network capacity, and continuity of care during events disrupting service delivery—

outbreaks of new diseases, for example, or floods and other natural catastrophes.



2.1. Definitions and scope

A clinically integrated set of capabilities that support the timely orchestration of patient care, including—but not limited to—continuity of care through disruptions, resource allocation during surges, and care coordination across providers, payers, and communities. In the context of the COVID-19 pandemic, the proposed integrated clinical-payer intelligence fabric powered the continuity of care through disruptions and the diagnosis and resource allocation for care surges. With resilience as a design principle, these capabilities supported similar functions during other large-scale emergencies. A broader set of use cases emerge during normal operating conditions: the intelligence fabric enables care coordination across a network of share-at-risk payers across a population of patients whose social and behavioral needs affect engagement in effective care.

The need for a resilient health service delivery network supporting timely continuity of care through disruptions and addressing resource allocation and care surge planning has been driven home by the COVID-19 pandemic. At the same time, the experience has highlighted the continuing barriers to



achieving these goals at scale: a lack of integration across clinical and claims-based data sources; inadequate attention to privacy, security, and the establishment of broad-based trust; and the absence of a supported capability for developing, evaluating, and maintaining the required range of descriptive, predictive, and prescriptive analytical capabilities.

Table 2. Components of the Unified Clinical-Payer Intelligence Fabric Architecture

Architecture Layer	Key Functions	Technologies / Standards	Benefits
Data Fabric	Data ingestion, storage, governance, sharing	OMOP, OHDSI, FHIR	Secure integrated datasets
Compute Fabric	Distributed computing and orchestration	Hadoop, Cloud Computing	Scalable analytics
Workflow Fabric	Pipeline automation and execution	Apache Airflow	Automated analytical workflows
Semantic Knowledge Fabric	Metadata management and semantic harmonization	Business glossaries, semantic mapping	Improved interoperability
Analytics Layer	Predictive, descriptive, causal analytics	AI/ML models	Decision intelligence

2.2. Rationale for an integrated clinical-payer intelligence ecosystem

Health providers, health plans, and payers should leverage the intelligence captured by clinical data and reimbursement signals to enhance care delivery. Timely access to health plan signals—such as network participation, prior authorizations, utilization management, retrospective claim denials, and post-discharge appointments—can help clinical care teams remain within the payer’s reimbursement framework and avoid unnecessary out-of-pocket expenses for patients. Sub-optimal care pathways lead to higher costs, reduced reimbursement, and poor experience, health litigation, and brand loss for service providers. Furthermore, such adverse plans are more likely to affect vulnerable groups. However, care continuity and patient-centered care become the cornerstones of service delivery during public health emergencies and service disruptions.

Among the key processes that constituents of the health ecosystem should initiate to build resilience during periods of crisis, such as pandemics and natural disasters, are the following: timely updates to clinical care delivery procedures in known high-transmission or high-prevalence zones, robust procedures for the transport and supply of essential goods and lifesaving drugs, appointment of standby restoration teams, contingency hiring and training of manpower, and allocation of appropriate resources based on prospective modeling scenarios. These clinical pathways, however, often are dispersed across stakeholder teams within the ecosystem and remain unexamined by management. Such continuity-of-care workflows need to be made explicit and approve—and even tested online—before a crisis.

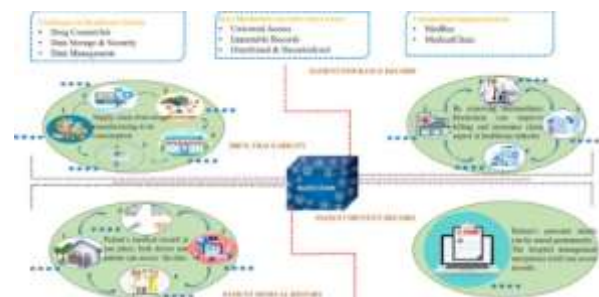


Fig 2: Healthcare Ecosystem - an overview



2.3. Key stakeholders and governance

Parties involved in the intelligence fabric's success share a common interest in enhancing the population's health while balancing cost. In addition to the health delivery system and the payers, who have a vested interest in improving the return on investment for healthcare spending, public health authorities can benefit from the early detection of anomalies and emerging health threats. Commercial interests in pharmaceuticals, vaccines, and medical supplies are stimulated by prior knowledge of potential demand changes. Health delivery systems, payer organizations, public health authorities, industry, and, ultimately, society at large have a shared mandate to support the delivery of safe, evidence-based, resilient health services that meet community requirements in times of crisis. They, therefore, share the responsibility for sustained investment in the development and maintenance of AI systems that might be called on whenever the health services of a population are put at risk.

Operational management, including the clinical and revenue cycle, the operation of health and non-health services, and the board and governance committees, have different and often conflicting priorities and time horizons. For this reason, the governance of the entire AI architecture should reside with an independent governing body rather than the traditional board structure of a single health organization. An AI governance board should be formed, endowed with influence and power, and comprising representatives from all key stakeholders. The board should govern the entire AI architecture and oversee funding, data submission and use, and the development of AI algorithms.

Equation 2: Predictive Demand Forecasting Model

The paper emphasizes predictive analytics for healthcare demand surges.

$$D_t = \alpha + \beta_1 C_t + \beta_2 P_t + \beta_3 S_t + \epsilon_t$$

Where:

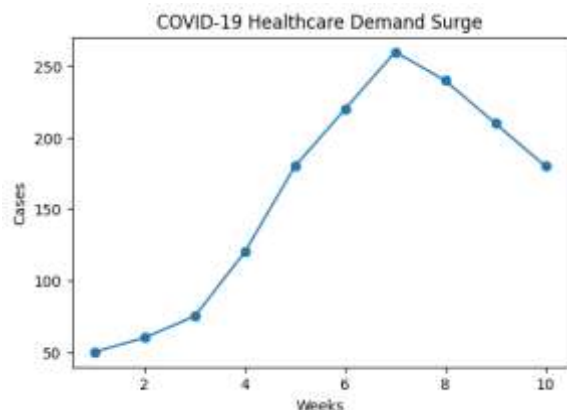
- D_t = predicted healthcare demand at time t

- C_t = clinical case volume
- P_t = payer reimbursement signal
- S_t = social determinant factors
- ϵ_t = random error

3. Architectural Principles

An integrated clinical-payer intelligence ecosystem must adhere to at least three key architectural principles. First, data coming from any source must be interoperable and follow standard syntaxes, semantics, structures, and exchange protocols. Second, spam and hate messages in any form must be prevented, and privacy, security, and ethical needs must be addressed consistently. Third, the solution must scale efficiently to any country and region while delivering timely, low-latency, and high-quality results.

Health services are delivered by multiple independent institutions, yet information systems at these institutions remain largely disconnected. This lack of interoperability is a key barrier in data integration and therefore in promoting value-based care. An integrated patient record system should address information needs in a standardized, secure, and responsible manner. Data coming from any source must be interoperable and follow standard syntaxes, semantics, structures, and exchange protocols. Approved uses of patient information should be clearly communicated to patients, who should also be informed when the same data are reused for another purpose. To maintain the trust of caregivers and patients, spam and hate messages in any form must be prevented, and privacy, security, and ethical needs must therefore be holistically addressed. To support public health during pandemics or major disasters, health services should be monitored and predicted on an ongoing basis, and oral health services and social determinants of health should also be included in the analysis and predictions. Equipped with such intelligence capabilities, health systems will be better prepared for any major future health service disruption.



3.1. Data interoperability and standards

Severe problems in health service delivery frequently arise from the absence of reliable, resilient, and scalable interoperability in the two key data sources that inform the vital decisions of numerous stakeholders: clinical data and payer data. A unified intelligence fabric provides the foundations for exploiting both clinical and payer data, thus strengthening health systems' capabilities for delivering, funding, and regulating health services.

Both clinical data streams and payer data often suffer from critical gaps or other deficiencies that can hinder their analytical utility. To mitigate such deficits, innovative AI- and ML-driven methods can be applied to enhance the completeness, accuracy, and validity of the underlying data and signals. For example, generated data such as IQVIA's PROVANTAGE database can supply integrated clinical-payer models with a scalable and temporally granular source to address the absence of timely clinical data for specific populations and disease conditions within a national or regional jurisdiction. These data initiatives represent adjacent innovations that can also be brought into unified analytical frameworks addressing resilience in health service delivery.



Fig 3: Interoperability in Healthcare Explained

3.2. Privacy, security, and ethical considerations

Healthcare organizations and their stakeholders are required to comply with several local and federally mandated regulations governing the protection of personally identifiable information. Health Insurance Portability and Accountability Act (HIPAA) regulations mandate the de-identification of health data whenever disclosure is required for purposes such as research or insurance reimbursement. Consent policies also include the a priori ban on datasharing unless opt-in consent has been explicitly provided or implied by law.

Data protection measures and associated monitoring can happen at different levels. Local data custodian institutions can define within their data governance framework the access model for different categories of data requestors. Some deterministically defined challenges might allow for an open data-sharing setting supported by naturally governed data use. More broadly, ethical aspects beyond compliance should guide data access and sharing: Is datasharing going to promote social good? Will the research questions and methods proposed adequately protect the privacy of individuals? Will individuals from whom data are being used benefit from the results of the analysis? A privacy-preserving framework for causal inference based on synthetic cohorts derived by collision-based recovery and others based on GRO are examples of emerging techniques for keeping data protected while allowing some forms of exploration under established constraints.

Table 3. Major Data Sources in the Intelligence Ecosystem



Data Source Category	Example Sources	Type of Information	Application
Clinical Data	EHRs, Telehealth Systems	Patient diagnosis, vitals, treatment history	Clinical monitoring and forecasting
Payer Data	Claims, reimbursement systems	Authorizations, claims, utilization	Financial and operational planning
Social Determinants Data	Socioeconomic indicators	Vulnerability and risk profiles	Population health management
External Environmental Data	Weather, outbreak data, mobility	Disaster and outbreak prediction	Surge planning
Sensor and IoT Data	Wearables, monitoring devices	Real-time physiological data	Remote monitoring

3.3. Scalability, resilience, and performance

Scalability, resilience, and performance are essential design principles for the proposed unified health clinical–payer intelligence fabric. Scalability addresses the changing data and processing needs of the system. The volume, variety, velocity, and veracity of data streams are expected to increase over time because the data landscape has been designed to accommodate new data sources as they become available. The analytical workflows are likely to require ever-more sophisticated predictive, prescriptive, and causal-exploration capabilities as the capabilities of supervised, unsupervised, and semi-supervised machine-learning techniques advance. Finally, as expressed by the Three Es of public health, the ability to understand longitudinal trends in health, use predictive analytics to anticipate changes in health-care

demand, and define prescriptive interventions in a proactive manner will be critical for resilience against future outbreaks, whether they be pandemics or other disruptions in continuity of care such as extreme weather events.

Resilience ensures that the intelligence fabric continues to function effectively even in the presence of lost, corrupted, or poorly functioning component services, and prevents a single point of failure from jeopardizing the whole. Duplication and timely replication of critical data elements, together with sufficient redundancy in processing capabilities, afford resilience without significant extra computing cost under normal circumstances. Ensuring resilience strengthens not only the information-architecture design but also the sense-making underpinning the deployed intelligent systems. These services need to remain available during events such as pandemic surges, when capacity is stretched, and need to continue to meet the 24/7 commitment to stakeholders. Performance addresses the speed of computation and delivery of insights to stakeholders.

Equation 3: Resource Allocation Optimization Function

The paper discusses optimal allocation of healthcare resources during crises.

$$\min Z = \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij}$$

Subject to:

$$\begin{aligned} \sum_{j=1}^n x_{ij} &\leq R_i \\ \sum_{i=1}^m x_{ij} &\geq D_j \end{aligned}$$

Where:

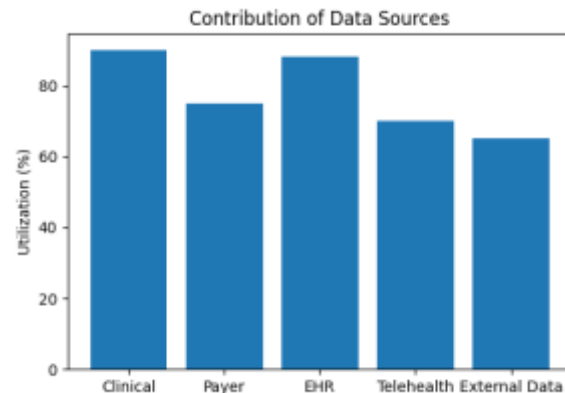
- x_{ij} = resources allocated from source i to demand point j
- c_{ij} = allocation cost
- R_i = available resources
- D_j = demand requirement

4. Data Sources and Ingestion

Completeness of the clinical-payer intelligence fabric requires ingestion of data from clinical, payer, and external sources. Three broad categories comprise the main components of the data ingestion layer.

Clinical data streams from electronic health records (EHRs) and telehealth systems represent a major component of the data ingestion layer, delivering individual and population-level time-sensitive health status and event information. Such data streams enable dashboards for early monitoring of patient conditions and detects trends indicating worsening patient status. Recent extensions provide EHR data integration with serum creatinine and pulmonary function test results to facilitate identification of patients at high risk for acute kidney injury or chronic obstructive pulmonary disease exacerbation.

In addition to clinical data, payer systems provide a comprehensive view of health services delivered or consumed—covering admissions, lengths of stay, surgeries, specialty consultation, laboratory test orders, and pharmacy issues—enabling descriptive analytics with a clearer view of who is receiving which health services for what conditions. Key signals sent from payer systems, such as approval or denial of preauthorization requests, share real-time insights about service necessity and acceptability by the clinical and payer communities. Such signals aid coordination of care by supporting provider–payer communication during the service cycle, particularly when clinical outcomes do not meet expectations.



4.1. Clinical data streams

An increasingly rich and diverse range of clinical data sources can enhance the breadth and depth of knowledge and intelligence for resilience, operational effectiveness, and value within and across health systems. Sensor-driven real-time data streams on physiological and behavioral health are already augmenting clinical data resources. Such data can generate process and outcome knowledge for real-time evaluations of experimental resumption of services and early detection of future surges in demand, and inform the allocation of limited health resources. External datasets from multiple sources and modalities can also further enrich health-specific features, enhancing predictive power and enabling tailor-made risk models for diverse sensitive population subgroups in decision-making.

Commercially available services can provide real-time tracking of COVID-19 surges, vaccination rates, and testing rates; vehicle collision hotspots; drought and weather risk assessments; drought/supply chain risk reduction assessments using technology and data; and risk identification/prevention and marketing strategies for drought relief schemes and services. Additional external datasets include daily nutrition supply-demand balances; livestock weather-based mortality probabilities; and vegetation maps. Enriched with relevant clinical, payer, and external datasets, predictive modelling investigations can address critical COVID-19-related issues



and other North American community health concerns, generating transferable fact-based knowledge. Clearly defined health issues with specific priority and predictive knowledge gaps can drive additional targeted collaborations with internal and external experts to fill these gaps.



Fig 4: CLINICAL DATA MANAGEMENT PROCESS OVERVIEW

4.2. Payer data and reimbursement signals

Estimated reimbursement streams derived from predictive models enable planning for alternative reimbursement strategies and related investments. Signals of impending reduced payments or higher risk contracts lead to proactive adjustments to operating plans, formalized through internal care protocols or submission for approval to appropriate outside agencies. Automated, near-real-time identification of new reimbursement opportunities, requiring urgent scale-up of capabilities and associated activity costs, directs proposals to appropriate stakeholders. Monitoring of reimbursements against budgetary expectations provides basis for resource reallocation and change of approval status on pathways by an internal territory management committee.

Health plans are paid for enrolling members into plans taking more risk, but most have infrastructure developed to minimize risk rather than optimize performance from taking risk. This is mainly because managing chronic populations is expensive and tough. By using some of the above data streams, plans that want to be more active with these populations (bring in

behaviorial resources, offer remote monitoring and management, etc.) can be tipped off when contracts and opportunities materialize, what type of investments and capabilities would be useful, and at what cost. These initial signals can be used to enable the “business case” behind making the needed investments. When funding contracts appear that require urgent scale-up, allow monitoring of that particular contract as part of day-to-day operations in real-time and simple time-consuming analysis and bid proposal at the time. Money spent does not turn into lost investments as monitoring and prevention evaluation helps maintain margins. Workforce management allows offering more services in non-peak times or at reduced costs.

Table 4. Analytical Frameworks Used in the Intelligence Fabric

Analytical Type	Objective	Methods Used	Example Use Case
Descriptive Analytics	Monitor trends and performance	Dashboards, visualization	COVID-19 monitoring
Predictive Analytics	Forecast future events	Machine learning, time-series models	Demand surge prediction
Prescriptive Analytics	Recommend optimal actions	Network flow optimization	Resource allocation
Causal Analytics	Evaluate interventions	Propensity score matching, instrumental variables	Vaccine uptake evaluation

4.3. Social determinants of health and external datasets

In addition to clinical and clinical-payer data sources, data on patients’ social determinants of health are increasingly captured and can play an important role in understanding their health status and associated needs. Other external data sources



can improve the understanding of health-care needing and associated costs, thereby enabling better real-time forecasting and operational support, for example, through improved weather prediction, policy-specific risk assessments (e.g., COVID-19 prevalence prediction, wildfires) or socioeconomic models related to violence, mental health, drugs, and other risk factors.

When fully leveraged, these social determinants and external data sources allow much deeper real-time situation awareness, including determination of socially vulnerable patients, care-required status, connected continuity-of-care, social support, availability of associated care resources (including for surge support) and other key factors that permit targeted preventive, operational and response interventions to improve patients' health, quality of life, and easing health-care need and costs. In this context, it is essential to possess a robust data-flow infrastructure at the regional level capable of integrating these multiple sources.

Equation 4: Interoperability Efficiency Equation

The paper repeatedly highlights interoperability between clinical and payer systems.

$$IE = \frac{I_s + S_h + D_q}{3}$$

Where:

- IE = interoperability efficiency
- I_s = interoperability standard compliance score
- S_h = semantic harmonization score
- D_q = data quality score

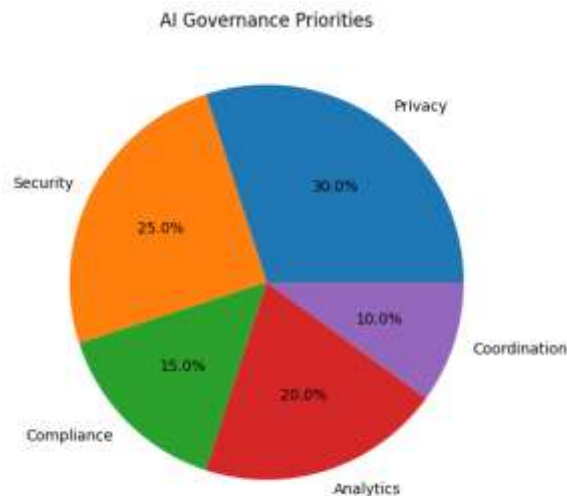
5. Analytical Frameworks

Data from clinical and payer sources can support three related types of analyses. Descriptive analytics, augmented by dashboards, identify unanticipated trends, gauge responses to

past perturbations, and track compliance with guidance. Predictive and prescriptive models formulate and assess scenarios of future trends and resource requirements, capturing external influences, stakeholder response, and counteractive measures. Causal inference analyses explore relationships among clinical outcomes, potentially augmented by social determinants of health, payer incentives, and intervention timing, and evaluate the effectiveness of interventions and pathways that qualify for coverage.

Descriptive analytics and dashboards comprise a fundamental set common to all organizations. Data mart health dashboards can visually depict changes, novel patterns of distress, the success of dynamic responses, and conformance with guidance, while rainfall, temperature, and epidemiological data maps can illustrate external features influencing clinical activities and outcomes. Data sources include clinical and reimbursement signals, and external datasets representing social determinants of health and other contextual factors. Descriptive analyses addressing specific inquiries can originate from ad-hoc requests or intuitive modeling by advanced users.

Finally, machine learning frameworks that use high-frequency summary signals for local viral load may help restore the relationship with the implicit sources of non-disruptive but unreported low-level excess demand described previously. Predictive analytics applied to pandemic-pertinent SDoHs can also help direct resources to mitigate the long-term effect of health-service disruption on vulnerable sections of society that may escape initial visual observation but contribute to future avoidable disability-adjusted life years.



Stakeholder	Primary Role	Benefits Received
Healthcare Providers	Deliver patient care	Improved operational intelligence
Payers / Insurers	Manage reimbursements and contracts	Better cost optimization
Public Health Authorities	Monitor population health	Early detection of outbreaks
Pharmaceutical Industry	Forecast medical demand	Optimized supply chain planning
Patients	Receive coordinated care	Better continuity and reduced costs
AI Governance Board	Oversee policies and ethics	Trustworthy AI operations

5.1. Descriptive analytics and dashboards

Within the unified intelligence fabric purported, the descriptive analytics layer offers dashboards that present an integrated view of clinical and payer data streams, while ensuring interoperability, privacy, and security. Data supply chain pipelines guarantee a continuous stream of high-fidelity data for dashboards that serve multiple stakeholders.

A first set of dashboards provides a system-wide view of the COVID-19 pandemic from both clinical and payer perspectives. Data blending and modeling functions within the data fabric guarantee the completeness and quality of clinical and payer data queried by the dashboards.

A second set of dashboards enables participating health services to assess the clinical and community-level factors associated with the number of COVID-19 cases reported in the previous week. These analyses will facilitate the revision of health service delivery strategies in a region that is currently facing renewed pressure from COVID-19.

Table 5. Stakeholders and Their Roles in the Unified Ecosystem

5.2. Predictive and prescriptive modeling

Conventional predictive models, including those based on supervised machine learning and time series methods, can identify high-risk patients and forthcoming demand surges by estimating the likelihood or severity of outcomes. Such predictions provide a foundation for scaling and partly automating health resource deployments. However, predictive outputs are most impactful when made actionable via prescriptive modeling.

A general class of prescriptive models can be cast as multiperiod, multicommodity, network flows problems in which resources—health providers, preventive interventions, vaccination services, equipment provision, and so on—flow through a dynamic network and in which flows for some periods and edges are predetermined. For example, consider a care-delivery network with many care types and conditions, and wherein patients typically select from prescribed treatment paths (e.g., waiting list, alternative hospital, or at

home with pre-emptive follow-up). The prescriptive problem is to determine external demand (or edgebreaks) and internal flows (on all paths and commodities) that minimize blues with patient preference.

Equation 5: Causal Effect Estimation Model

The paper discusses causal inference using propensity score matching and intervention evaluation.

$$ATE = E[Y(1) - Y(0)]$$

Where:

- ATE = Average Treatment Effect
- $Y(1)$ = outcome with intervention
- $Y(0)$ = outcome without intervention

5.3. Causal inference and evaluation of interventions

Establishing causality—not just correlation—is critical for developing effective interventions in health service delivery, yet such evaluations remain scarce. Harnessing data from across the clinical-payer spectrum enables causal analyses using approaches such as propensity score matching and instrumental variable analysis. Isolated care delivery interventions have been assessed using such methods, but new tools bring together relevant stakeholders, thereby expanding the range of questions that can be addressed. For example, COVID-19 vaccine uptake improved with increased access to transportation services, with implications for the subsequent management of vaccine hesitancy within the broader community.

Propensity score-based methods are also being explored to initiate clinical management of patients with untreated diabetes. Initiatives to strengthen care coordination are expected to be evaluable via instrumental variable techniques. Complementary research is leveraging qualitative data sources (e.g., community discussions) to discover potential

causal mechanisms and robust interventions that are either currently available or can be developed.

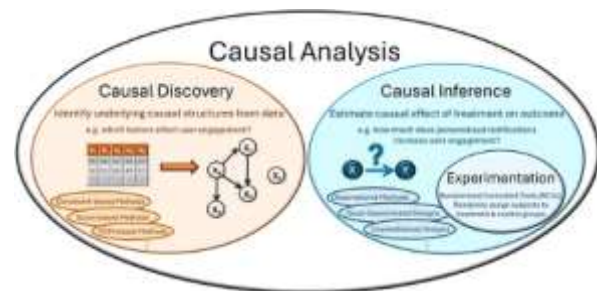


Fig 5: Causal analysis overview

6. The Unified Intelligence Fabric Architecture

A layered architectural representation clarifies how the various design principles and guidelines converge into an integrated solution framework. The fabric design encompasses many of the elements of a data lake architecture: data sources, ingestion, storage, processing, and serving. The elements that help facilitate data and semantic interoperability are specifically highlighted. Core components include

1. **Data fabric and semantics harmonization:**

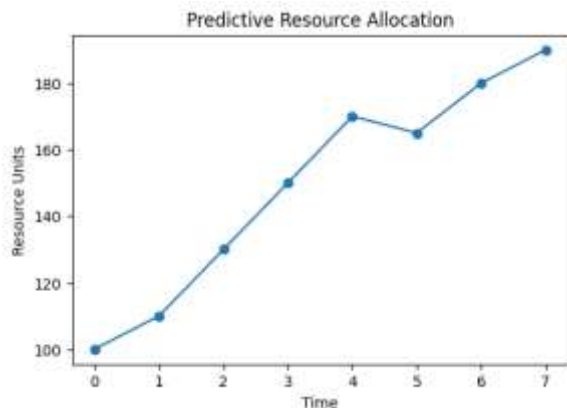
The data fabric integrates clinical sources—the open-source OHDSI infrastructure provides a key example—and payer repositories, enabling continuity of care and facilitating improved analytics. External datasets such as SDOH and oceanography serve as supplements. Semantic harmonization applies both industry standards (such as OMOP for clinical data) and unified business glossaries to improve data interoperability. Supports both description and preservation of provenance.

2. **Compute, storage, and workflow orchestration:**

Computes involving large datasets place considerable burdens on local processing units and networking infrastructure. Computing cluster solutions (such as Hadoop) augment local processing capabilities. Mix of cloud-based and edge-based solutions accommodate different types of data. Services such as Apache Airflow support coordination of multi-step data workflows.

3. **Tools and capabilities:**

Central repositories for development enhance collaboration, reduce redundancy, and share knowledge. Centralization of risk/profit-share dashboards simplifies updating and improves consistency. Skills development resources, including model repositories, help improve capabilities across organizations.



6.1. Layered architectural view

The unified clinical-payer intelligence fabric consists of four layers (Figure 1): (1) a data fabric supporting secure data ingestion, integration, governance, storage, access, and sharing, (2) a compute fabric orchestrating compute resources hosted by multiple providers across multiple sites, (3) a workflow fabric enabling seamless end-to-end execution of analytical pipelines, and (4) a semantic knowledge fabric maintaining semantic metadata needed for effective use and re-use of assets.

The data fabric supports ingestion and harmonization of both payer and clinical data streams in compliance with privacy, security, and trust concerns related to the use of sensitive health information. Data ingestion and publishing are governed using flexible policy mechanisms that enable dynamic governance of sensitive data flows for the duration of an analytical pipeline. Sensitivity, security, and access controls attached to data sources guide privacy-preserving statistical disclosure control mechanisms. By creating a virtual data space covering data held by multiple trusted partners, replication and movement of data are minimized, allowing control over data provenance while improving efficiency and resource use.

Table 6. Resilience Use Cases of the Clinical-Payer Intelligence Fabric

Use Case	Problem Addressed	Intelligence Capability	Expected Benefit
Continuity of Care	Service disruption during crises	Real-time pathway monitoring	Reduced mortality and delays
Surge Planning	Resource shortages	Predictive resource modeling	Improved preparedness
Care Coordination	Fragmented treatment pathways	Workflow surveillance	Better clinical outcomes
Pandemic Response	COVID-19 operational disruptions	Integrated analytics dashboards	Faster response decisions
Vulnerable Population Support	Hidden socioeconomic risks	SDOH-based predictive models	Reduced disparities

6.2. Data fabric and semantic harmonization



A unified clinical-payer intelligence ecosystem requires a corresponding data architecture. Such a data fabric acts as an enabler by securely unifying, harmonizing, and making data available for effective and efficient clinical-payer analytics.

Clinical and payer datasets—often stored in disparate locations and data silos—must be appropriately identified and made available for access, discovery, and use within the analytics fabric. These datasets span varied modalities and structures, and semantic harmonization is critical to establishing a unified view of health service delivery, in addition to facilitating more advanced analytics such as causal inference.

Altaf et al. illustrate the role of semantic harmonization in determining the feasibility of an end-to-end learning machine and vice-versa. A minimal effort is involved in creating harmonization rules for the established “what-happened-why-if” machine that enables causal inference. A clinical-payer intelligence fabric can be interpreted through the lenses of a descriptive analytics layer and comparable design principles, focusing specifically on semantic harmonization and the resulting data fabric.



Fig 6: Data Fabric Architecture

6.3. Compute, storage, and workflow orchestration

A unified intelligence fabric needs a robust, scalable compute and storage infrastructure with automation of key processes.

The compute and storage resource orchestration can be through on-premises private cloud infrastructure, public cloud infrastructure, or a hybrid solution, depending on the type and scale of service delivery and data stored and processed. A unified enterprise service bus needs to automate the orchestration of data processing and actions based on defined Policy or event-based triggers. Autonomy in system configurations common to many applications enhances reliability and responsiveness of various workloads.

Pre-processing involves data engineering: cleaning, wrangling, enriching (harmonizing, exploratory analysis, refining labels, joining with domain knowledge for machine-learning-based features), and transforming for analytics. Temporal data, ubiquitous in the domain, need special treatment—construction of time series for use cases such as forecasting—pouring data into forms that general analytics engines handle well. Data are tagged with metadata for location, temporal aspects, and contributors for security and privacy concerns and for subsequent inferencing of intent.





7. Use Cases for Resilient Health Service Delivery

A unified fabric of clinical-payer intelligence could demonstrate its value at both clinical and operational levels by analyzing real health systems under both routine and stress conditions. Three potential use cases in ongoing and future work illustrate how such a setup could facilitate continuity of care during widespread service disruption, enable proactive resource allocation and surge planning, and assist in coordinating care pathways across organizations.

Amid the COVID-19 pandemic, the delivery of many health services—especially elective surgery—has ceased, causing backlogs and delays. Such interruptions heighten the risks of mortality and morbidity of unmet clinical needs. Although health services already have formal arrangements with private sector facilities to ensure continuity during surges, other approved partnerships have sometimes broken down at a local level owing to lack of communication, coordination, and trust. A clinical-payer intelligence fabric could assist health services in identifying these external partners through a process similar to a health impact assessment of major developments, enabling assessments of financial stability, clinical capability and capacity, and current demand for services. This resourcing information could also help health services to enter, and maintain, a resilient partnership with other clinical organizations.



7.1. Continuity of care during disruptions

Continuity of care during interruptions in service delivery, whether due to seasonal, annual, or ad-hoc external shocks, is a prime consideration for resilient health systems. Although these shocks may be temporary, the effects can have widespread repercussions across segments of the care continuum. Proactive measures must therefore ensure that anticipated shifts in care demand are met by upstream supply–demand alignment and supportive care pathways throughout the system.

Clinical–payer intelligence frameworks enable near real-time computation of approved patient pathways based on clinical and patient characteristics, care utilization, fund allocation, and current demand for care. Such information underpinned improved health outcomes and economic efficiency for a region experiencing a severe norovirus outbreak, affording joint clinical–payer visibility of care overflow and capacity constraints, and creating continuums of care between emergency and high-acuity admission sites. Penned by Midwestern high-acuity care providers and a national payer, these joint pathways were adopted in other cases of seasonal norovirus outbreaks and where resource shortages necessitated triage at the onset of more serious conditions.



7.2. Resource allocation and surge planning

1. Resource allocation and surge planning

An often-overlooked aspect of resilience is the ability to replenish medical resources after a disruptive event. These resources may take the form of people (healthcare workers), substances (such as vaccines), or devices (e.g. prosthetic limbs). Analytics that enable rapid assessment of resource utilization during events of interest and the ability to model surge demand for all three types of resources mentioned earlier might help prepare for the post-event resource drain. Such models might also improve resource allocation prior to anticipated demand surges, a long-standing challenge facing hospitals across the globe. Hospitals are rewardingly compensated for maintaining a minimum number of intensive care beds, but little attention has yet been paid to the wider implications of providing the necessary trained staff, medications, and knowledge to respond to external events of medical interest.

7.3. Care coordination and approved pathways

During routine service delivery, a wide variety of care approaches are possible, leading to redundancy, variation, and sometimes waste. Despite evidence supporting the effectiveness of specific management strategies and pathways for major conditions (such as care co-ordination protocols for care transition or those for managing pneumonia, stroke, and sepsis), they are not always followed. Care administered outside evidence-based guidelines is often suboptimal and can lead to adverse outcomes. External disturbances, such as pandemics or natural disasters, highlight weaknesses in the health ecosystem and can force service delivery along different routes. Surveillance of these emerging pathways allows lessons to be drawn and used to update needed care pathways.

A real-time analysis of the care pathways being followed, using SNS, administrative, and health outcome data, informs stakeholders. Particular areas of concern can be flagged for investigation, and communication can be sent to services

about near real-time treatment patterns and outcomes. For example, the analysis may find lower admission rates of people with stroke or pneumonia to a designated high-dependency service. This prompts a deeper investigation that shows these patients are being treated at smaller hospitals without access to such services and that there are resulting adverse health outcomes. Lessons drawn can be used to update the approved pathways and supporting documents used by service coordinators.

8. Conclusion

Health information technology promotes efficiency for all stakeholders through business process optimization, prediction, and improved decision-making. However, existing initiatives and investments have failed to provide an interoperable operating environment for the health sector ecosystem. A unified intelligence fabric is required. It spans clinical and payer domains, meshes data and signals from diverse sources, and deploys rich descriptive, predictive, prescriptive, and causal analytical frameworks. Together these capabilities underpin business process optimization, prediction, and decision support for resiliency. Use cases examine continuity of care during disruptions, resource allocation and surge planning, and coordinated pathway selection.

Digital health economies continue to face unprecedented shocks. COVID-19 – and the many health ecosystem breakdowns it highlights – impose rising demands and shrinking margins on all actors. Yet existing initiatives and investments have failed to deliver an interoperable operating environment for the ecosystem that subnetworks and connects the core players – payers, providers, and patients (consumers) – and their relationships for the production, distribution, and consumption of health services. Without such an interoperable intelligence environment that enables sharing, pooling, and synergizing clinical and payer data, signals, and competencies, these actors are resource-constrained in their attempts to develop, coordinate, govern, evaluate, and pay for resilient service delivery.



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