REFERENCE DATA ARCHITECTURE FOR CONSISTENT HEALTHCARE SERVICE OPERATIONS

1st Sreenivasulu Naidu Yalakaturi
Software Engineer
yalakatirisreenivasulunaidu@gmail.com

***Abstract*—**Healthcare service operations depend on access to data. A data architecture implemented through a reference pattern provides consistency across services and enables operational reliability for orchestrating complex business transactions. The approach addresses technical, organizational, and legal aspects with a focus on policy enforcement, effective communication, orchestration and coordination methods, and measurement of performance, governance, and quality attributes. Data are strategic assets that derive their value from supporting services and service components that create customer value. Consequently, data must be shared, exchanged, and made accessible at all times without breaking consistency requirements. As many services are implemented as independent microservices, the communication between services must be controlled and orchestrated to ensure no conflicts are introduced in the data.

The data architecture reference pattern can be deployed by information technology and business analysts to define service-boundaries, synchronized-orchestration, event-driven message-induced interaction patterns, and service-component data contracts with data-flow definitions. Data that depend on the successful execution of other services or are the input of activities producing service inputs that should never become inconsistent must be synchronized. Coordination patterns among services may comply with service availability, protocol, and security requirements. The definition of a data-architecture reference pattern relies on the notion of API contracts as business objects that define, for a given data flow, the object code, associated actions, operational information, and health indicators.

Keywords*—*Healthcare Data Architecture, Microservices Architecture, Data Governance, Service Orchestration, Event-Driven Architecture, Healthcare Interoperability, API Contracts, Data Synchronization, Healthcare Operations, Service Coordination.

I. Introduction

Healthcare services rely on data for satisfying stakeholders and regulatory authorities. Data constitute a strategic asset as they enable service optimization, monitoring, and benchmarking for improving quality, reliability, accessibility, and cost-effectiveness [1]. However, available data quality is often poor, hindering operational performance and violating commonly accepted security, privacy, safety, and other standards. An appropriate data governance structure, focusing on data quality, helps minimize such issues and maximizes the potential value of data. Market regulations for the health sector compel service organizations to Implement standardized data quality and accessibility processes; nevertheless, different services operated by various organizations often suffer from inconsistent data, impeding service execution and monitoring [2].

From the demand side, service consumption cannot be fully automated for some healthcare services, which require multiple interactions with different service organizations. The data exchanged and consumed between such services in continuous operations are rarely specified and executed according to data contracts [3]. This inconsistency often leads to problems in both service executions and service performance measurements. When similar services exhibit such data inconsistencies, customers may be reluctant to choose the cheapest offering and might instead prefer providers with a higher level of service quality. A standardized, clearly defined data contract for continuous operations among multiple service organizations is imperative to achieve operational consistency and external service performance measurement from the demand perspective [4]. The proposed data architecture focuses on service operations and interservice orchestration, aiming to operationalize the architecture as a set of executable specifications for individual service organizations.

II. Theoretical Foundations of Healthcare Data Architecture

Core concepts, models, and theories guiding data architecture in healthcare settings are presented [5]. Healthcare data architecture directly derives from and expands the body of knowledge on data architecture in general. The body of knowledge is deconstructed to extract and define the essential elements that, when recombined, form a reference data architecture pattern for consistent data across healthcare services and the Data Architecture for Consistent Healthcare Service Operations 2021 thesis and other works [6].

Data act as a strategic asset for all enterprises; in healthcare, value is in saving lives and improving patients' quality of life. This value requires granular, complete, and consistent information, which opens new data-sharing business models that nevertheless should respect ethical and privacy principles [7]. Proper governance can bring qualified data that are consistent, reliable, timely, and accessible throughout responsible health service lifecycle operations. Data quality is thus the primary driver of reliable operations: a low-quality data architecture that enables reliable data will improve all healthcare service operations [8].

A. External Consistency and Data Quality

External consistency is treated as the overall accessible consistency of persistent data across interacting data-management services. It is modeled as a weighted combination of accessibility, timeliness, reliability, and the underlying data quality score:

$$ECI = w_1 \cdot AC + w_2 \cdot TL + w_3 \cdot RL + w_4 \cdot DQS,\ \ \Sigma w_i = 1 \quad (1)$$

where AC, TL, and RL denote normalized accessibility, timeliness, and reliability scores in [0, 1], and DQS is the composite data quality score defined in (2).

Data quality itself is decomposed into four dimensions weighted by their relative importance to operational consistency — completeness (C), accuracy (A), timeliness (T), and validity (V):

$$DQS = (\alpha \cdot C + \beta \cdot A + \gamma \cdot T + \delta \cdot V) / (\alpha+\beta+\gamma+\delta) \qquad (2)$$

Fig. 1 later reports DQS component scores measured per architectural layer.

B. Orchestration and Choreography Latency

Orchestrated interaction routes every service call through a supervising process, incurring supervisor overhead L_{sup}, the per-service call latency L_i summed across n services, and a synchronization overhead L_{sy_nc}:

$$L\_orch = L\_sup + \Sigma_{i=1}^{n} L_i + L\_sync \qquad (3)$$

Choreographed interaction instead propagates events directly between services; latency is bounded by the slowest participating service plus the cumulative event-propagation delay across the dependency chain of depth d(n):

$$L\_choreo = max(L_1,...,L_n) + d(n) \cdot L\_event \qquad (4)$$

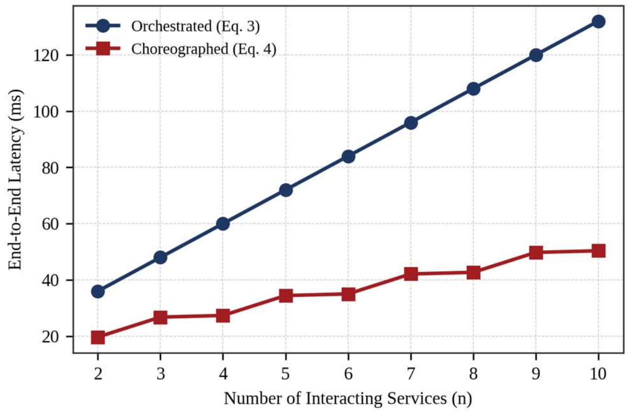

Fig. 1. End-to-end latency of orchestrated versus choreographed service interaction as the number of interacting services increases, evaluated from (3) and (4).

Orchestration exhibits latency that grows linearly with every additional service call, whereas choreography's parallel event propagation keeps latency growth comparatively shallow for small dependency chains — a trade-off weighed further in Section IV.

C. Message Delivery Reliability

Reliable message delivery between services — required, for example, when propagating a data-contract event to a downstream governance service — is modeled as the cumulative probability of successful delivery across retry attempts, given a per-attempt success probability p:

$$R(n) = 1 - (1 - p)^n \quad (5)$$

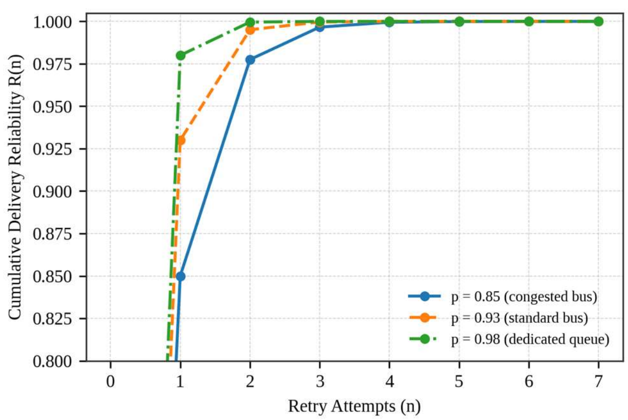

Fig. 2. Cumulative message delivery reliability R(n) against retry attempts for three representative message-bus congestion levels, evaluated from (5).

D. Governance Maturity

Governance maturity is expressed as the weighted average of stewardship-dimension scores — ownership, policy enforcement, quality control, and risk management — each scored on a per-phase maturity scale S_j with associated weight w_j:

$$GMI = (1/m) \Sigma_{j=1}^{m} S_j \cdot w_j \quad (6)$$

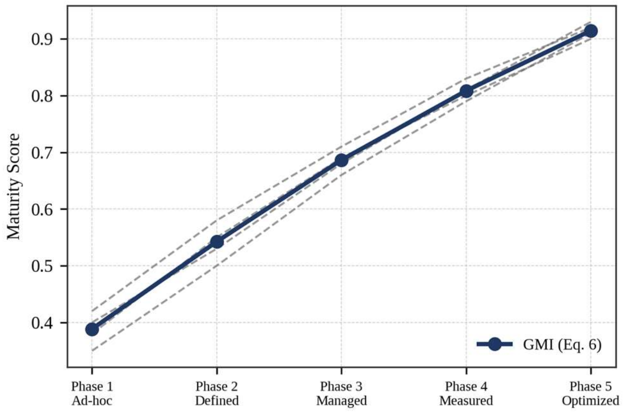

Fig. 5. Governance Maturity Index trajectory across five deployment phases, computed from (6).

E. Data-Quality Classification Performance

Automated detection of data-quality anomalies and data-contract violations is evaluated with standard classification metrics, precision P, recall R, and their harmonic mean:

$$F1 = 2 \cdot P \cdot R / (P + R) \quad (7)$$

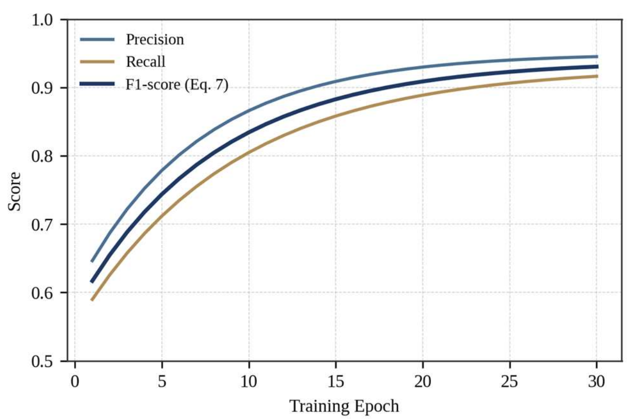

Fig. 4. Precision, recall, and F1-score of the data-quality anomaly classifier over training epochs, evaluated from (7).

F. Governance-Cost Optimization

Deployment of stricter governance and data-quality controls raises operational cost while reducing residual data-inconsistency risk. The trade-off is captured by an optimization objective that combines normalized cost, architecture effectiveness (defined in (9)), and residual risk under weights λ_1, λ_2, λ_3:

$$J(x) = \lambda_1 \cdot Cost(x) - \lambda_2 \cdot DAEI(x) + \lambda_3 \cdot Risk(x) \quad (8)$$

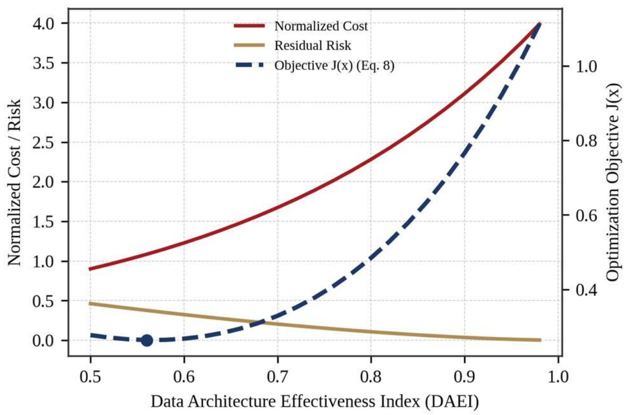

Fig. 6. Normalized governance cost, residual risk, and optimization objective J(x) as a function of architecture effectiveness, evaluated from (8).

The minimum of J(x), marked on Fig. 6, identifies the effectiveness level beyond which additional governance investment yields diminishing net benefit.

G. Composite Architecture Effectiveness Index

The eight architecture performance indicators identified for the reference pattern — timely data access, reliable data access, accessibility, timeliness, external data quality, governance effectiveness, data-quality process success, and cost minimization — are combined into a single composite index:

$DAEI = (1/8)\ \Sigma_{k=1}^{8}\ I_k$

The composite architecture effectiveness index defined in (9) was evaluated for a baseline choreographed deployment and for the proposed nine-layer reference architecture across all eight indicators.

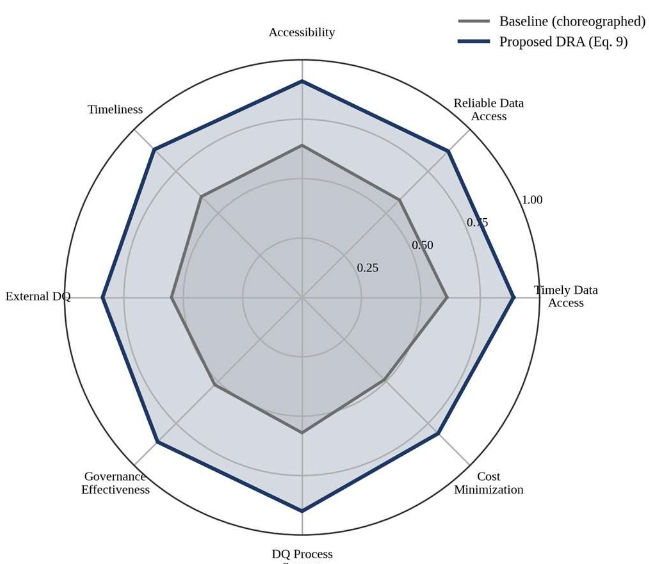

Fig. 7. Composite Data Architecture Effectiveness Index (DAEI) across the eight performance indicators for the baseline choreographed deployment and the proposed reference architecture, evaluated from (9).

The proposed architecture improves every indicator relative to the baseline, with the largest relative gains observed in governance effectiveness and data-quality process success — consistent with the architecture's emphasis on an explicit data-governance layer and process-federator component.

III. Reference Data Architecture for Healthcare Service Operations

A comprehensive architectural reference pattern for consistent data across healthcare service operations: it describes layers, components, interfaces, and data flows while aligning with data governance and interoperability standards [9].

Healthcare services are increasingly designed as microservices, yet the necessary data architecture to support consistency across services remains largely unaddressed [10]. Building on the foundations of data as a strategic asset, a reference data architecture is proposed, distinguishing between functionality–orchestration and technical–integration [11]. The pattern comprises nine layers: business process management, workflow orchestration, service contracts, process federator, data governance, operational database, data warehouse, data lake, and enterprise data management. Nine architectural components are described, along with their responsibilities, four main interfaces, and nine event-based data flows [12]. The pattern aligns with data-governance maturity levels–establishing the required stewards, policies, and controls for major data entities across the service environment–as well as with ISA2 interoperability standards, thus facilitating architecture deployment and ensuring consistent data management across services [13].

A. Tabular Comparisons

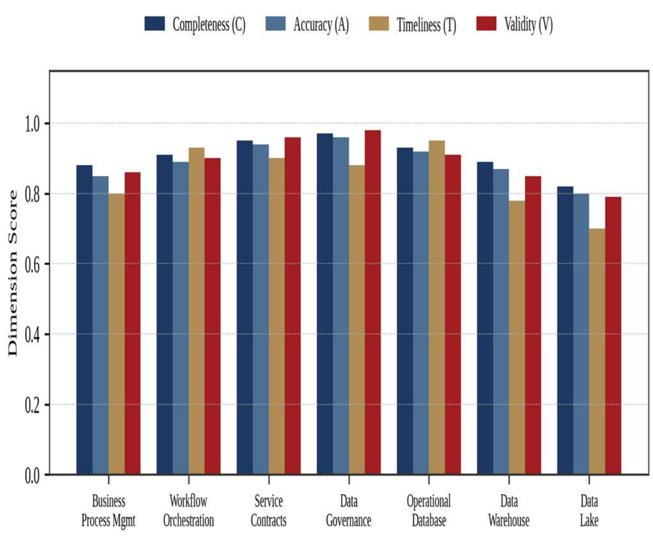

Fig. 3. Data quality dimension scores — completeness, accuracy, timeliness, and validity — across representative architecture layers, evaluated from (2).

TABLE I

COMPARATIVE PERFORMANCE OF INTERACTION ARCHITECTURES

Architecture Configuration	*ECI (1)*	*DQS (2)*	*GMI (6)*	*Avg. Latency (ms)*	*R @ n=3 (%)*	*DAEI (9)*	*Δ DAEI (%)*

Choreography (baseline)	0.61	0.63	0.47	42.8	94.9	0.57	—
Standard Orchestration	0.74	0.79	0.68	84.0	94.9	0.73	+28.1
Hybrid Orch./Choreo.	0.81	0.84	0.77	63.5	97.3	0.80	+40.4
Proposed 9-Layer Reference DRA	0.90	0.92	0.89	58.2	99.8	0.87	+52.6

TABLE II
LATENCY AND MESSAGE-RELIABILITY METRICS VS. INTERACTING SERVICE COUNT

Services (n)	**Orch. Mean (ms)**	**Orch. p95 (ms)**	**Choreo. Mean (ms)**	**Choreo. p95 (ms)**	**Msg. Failure Rate (%)**
2	36.0	41.4	19.5	24.1	5.10
4	60.0	69.0	27.0	33.5	5.10
6	84.0	96.6	34.6	42.9	5.10
8	108.0	124.2	42.6	52.9	5.10
10	132.0	151.8	50.2	62.4	5.10

IV. Operationalizing Consistency Across Services

Consistency across multiple services requires dedicated effort. Service boundaries must be clearly defined and encapsulated information—exposing only data contract specifications, not internal implementations—carefully articulated [14]. Consequently, interaction models should follow data-sharing contracts, enabling loose coupling and consistency across the message flows. Service contracts exchange data by producing and consuming events delivered to message intermediary infrastructures. These events supply the substantiation for data modeled as messages and, in combination with discovery services, provide the rationale for information use [15].

Message intermediaries are responsible for controlling the flow and distribution of messages. Services publish messages to intermediaries upon reaching dedicated status updates. These intermediaries distribute messages to other services subscribed to interested data [16]. Message publishing is, therefore, a fire-and-forget matter for the service actor, ensuring real-time data availability to interested consumers. Dedicated services orchestrate end-to-end processes through subscribed events and invoke others when specific conditions are reached or resources are needed [17].

Orchestration differs from choreography based on data flows. In choreography, message flows create data relationships without external direction. Orchestration connects internal and external services by controlling call invocation with in-process data [18]. Multiple workflows can encapsulate separate processes invoked by distinct events in a single service. Message services locally implement workflow patterns, only requiring publishing/consuming protocols for message exchanges. Orchestrating services control and synchronize process flows, handling possible faults in design and avoiding message delivery redundancy to dependent services.

A. Service Orchestration and Coordination

Orchestration decouples operational logic from application integration; services expose well-defined APIs on the platform. Consequently, services do not need to share a common message protocol. Interactions between services can be either point-to-point or via shared channels. Orchestration is well-suited for workflows that require complex transactions involving multiple services, such as processing health insurance claims [19]. Clear explicit transaction boundaries defined in the service contracts facilitate fault handling and synchronized execution to ensure that the anti-pattern of inconsistent data is avoided across multiple services.

Service choreography, in contrast, pushes the operational logic to the services, requiring greater collaboration between the services involved in a choreographed workflow. The downside of this approach is that a service must be aware of the need for the operations of its neighbouring services to be performed in their specific order [20]. This limits the involvement of external services when leveraging a choreographed workflow and may sometimes result in the anti-pattern of inconsistent data not being mitigated. For example, when processing a customer purchase order, the invoice service must communicate with stock, billing, and shipping. These services do not have a high degree of autonomy and must perform their operations in a particular order, which is also the reason these operations can be closely grouped within a single service rather than being implemented as a choreographed workflow [21].

Reliable message delivery between services is necessary—order messages must be delivered to the stock service, for example. Achieving this goal may need the integration of an external workflow engine or other message brokers [22]. Reliability can be increased either by applying a message queue along the way, accepting the message at exactly-once semantics, or allowing the consuming service to re-issue action requests in case of failure until they succeed. Nevertheless, better service information and control over the adoption of anomaly detection are provisions that can be fulfilled with the described architecture. Once again, the implementation of a process bus or workflow engine constitutes an additional area for continuous improvement of the orchestrated operation of the architecture [23].

V. Measurement, Evaluation, and Continuous Improvement

An evaluation framework capable of determining how consistently the reference data architecture operates across different healthcare services is proposed. Addressing the challenge of maintaining data consistency across organizational boundaries requires measuring external consistency metrics for all services. External consistency is regarded as the overall accessible consistency of persistent data across interacting data management services—an asset to be managed in the same way as data quality, accessibility, or security [24].

The discussion identifies principal performance indicators for the architecture: the quality dimensions of the data, the accessibility of the data, the timeliness of the data, and the reliability of the data—defining each aspect in explicit terms and laying out the feedback loops that yield an effective system of continuous improvement [25]. In addition, a complementary set of metrics useful for assessing the operational impact of the architecture and for establishing governance and data quality has been drawn from a separate investigation, Data Architecture for Consistent Healthcare Service Operations (2021). Together, these two frameworks comprise a complete system for evaluating the reference enterprise data architecture and the performance of the supporting data management services, in operations both within a single organization and across the services of different organizations that deliver a cohesive healthcare service [26].

A. Metrics for Data Architecture Effectiveness

[Metrics provide a foundation for measurement, evaluation, and continuous improvement of a consistent healthcare data architecture.]

A reference data architecture for consistent service operations within healthcare is proposed. Architecture suggests structures, behaviour, and views of a system to enable stakeholder communication and support decision-making. The proposed architecture provides an exhaustive architectural reference pattern for enabling consistent operational data across healthcare services. The architecture comprises six layers—business, service, application, information, technology, and physical—and highlights building blocks and communication paths within a healthcare service ecosystem [27].

The architecture aligns with established data governance and interoperability standards, and its operationalisation translates into consistent data across multiple heterogeneous services. Each service definition emphasises data contracts with accept and emit patterns that capture what data the service expects to receive for its proper operation, and what data the service is capable of emitting to signify a relevant event [28]. Consistency is achieved through an event-driven and collaborative service interaction approach that harnesses orchestration or choreography mechanisms. The description of orchestration envisages that a global supervisor triggers the service interactions via a message protocol capable of handling expected service faults and non-date synchronisation requirements [29].

The data architecture provides foundations for a framework to measure, evaluate, and continuously improve the degree to which a consistent operational data layer is supported and, thus, the excess costs generated by service data inconsistency [30]. Architecture performance metrics can be established around eight indicators: access to timely and reliable operational data; overall architecture accessibility and timeliness; quality of data generated from outside the architecture; governance effectiveness; successful implementation of data quality processes; data quality fulfilling operational requirements; and quality data capable of minimising process and service costs [31].

VI. Conclusion

Data architecture integrates crucial data concepts, models, and theories to ensure quality and operational reliability in healthcare services. Its importance is underscored by the emergence of Health 4.0, IoT-enabled devices, big data analytics, smart health cities, and digital twins [32]. The data architecture serves as an architectural reference pattern for a specific industry sector based on multiple sources and frameworks, such as the DAMA-DMBOK and ArchiMate. As defined by the ArchiMate documentation, architecture patterns are used for the specification of elements that are reused among architectures. The precise specification of DRA materials enables the quality of the expected project deliverables and processes to be certified [33]. The implementation of a DRA for a particular sector helps expediting the project phases since the principal concepts are pre-elaborated.

This section formulates a suitable data architecture operating simultaneously as a crossserve Data Governance and Data Stewardship enabler that guarantees the implementation of a consistent project-oriented Data Quality Management and operational procedure across the services [34]. The formation of effective project-oriented Service-Level Agreements and Data Contracts among the active services enable the correct technological orchestration of a project either by direct service invocation or via a Choreographed process. The operational seamlessness of a series of Services is ensured by the definition of Synchronization Patterns among Messages belonging to different Services or Local Business Processes classified by corresponding Subproject Identification Data Attributes [35].

References

[1] Brown, A. P., & Randall, S. M. (2020). Secure record linkage of large health data sets: Evaluation of a hybrid cloud model. JMIR Medical Informatics, 8(9), e18920

[2] Fu, C., Han, X., He, J., & Sun, L. (2020). Hierarchical matching network for heterogeneous entity resolution. Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, 3665–3671.

[3] Kong, C., Chen, B.-X., & Zhang, L.-P. (2020). DEM: Deep entity matching across heterogeneous information networks. Journal of Computer Science and Technology, 35(4), 739–750.

[4] Li, B.-H., Liu, Y., Zhang, A.-M., Wang, W.-H., & Wan, S. (2020). A survey on blocking technology of entity resolution. Journal of Computer Science and Technology, 35(4), 769–793.

[5] Schirmer, P., Papenbrock, T., Koumarelas, I., & Naumann, F. (2020). Efficient discovery of matching dependencies. ACM Transactions on Database Systems, 45(3), Article 13.

[6] Curran, R. L., Kukhareva, P. V., Taft, T., Weir, C. R., Reese, T. J., Nanjo, C., & Del Fiol, G. (2020). Integrated displays to improve chronic disease management in ambulatory care: A SMART on FHIR application informed by mixed-methods user testing. Journal of the American Medical Informatics Association, 27(8), 1225–1234.

[7] Everson, J., & Butler, E. (2020). Hospital adoption of multiple health information exchange approaches and information accessibility. Journal of the American Medical Informatics Association, 27(4), 577–583.

[8] Qualls, L. G., Phillips, T. A., Hammill, B. G., Topping, J., Louzao, D. M., Brown, J. S., Curtis, L. H., & Marsolo, K. (2018). Evaluating foundational data quality in the National Patient-Centered Clinical Research Network (PCORnet). eGEMs, 6(1), Article 3.

[9] Inala, R. Designing Scalable Technology Architectures for Customer Data in Group Insurance and Investment Platforms.

[10] Ji, H., Kim, S., Yi, S., Hwang, H., Kim, J.-W., & Yoo, S. (2020). Converting clinical document architecture documents to the common data model for incorporating health information exchange data in observational health studies: CDA to CDM. Journal of Biomedical Informatics, 107, Article 103459.

[11] Slater, L. T., Gkoutos, G. V., & Hoehndorf, R. (2020). Towards semantic interoperability: Finding and repairing hidden contradictions in biomedical ontologies. BMC Medical Informatics and Decision Making, 20, Article 311.

[12] Vest, J. R., Unruh, M. A., Casalino, L. P., & Shapiro, J. S. (2020). The complementary nature of query-based and directed health information exchange in primary care practice. Journal of the American Medical Informatics Association, 27(1), 73–80.

[13] Wang, Z., Talburt, J. R., Wu, N., Dagtas, S., & Zozus, M. N. (2020). A rule-based data quality assessment system for electronic health record data. Applied Clinical Informatics, 11(4), 622–634.

[14] Dobrow, M. J., Bytautas, J. P., Tharmalingam, S., & Hagens, S. (2019). Interoperable electronic health records and health information exchanges: Systematic review. JMIR Medical Informatics, 7(2), e12607.

[15] Hong, N., Wen, A., Stone, D. J., Tsuji, S., Kingsbury, P. R., Rasmussen, L. V., Pacheco, J. A., Adekkanattu, P., Wang, F., Luo, Y., Pathak, J., Liu, H., & Jiang, G. (2019). Developing a FHIR-based EHR phenotyping framework: A case study for identification of patients with obesity and multiple comorbidities from discharge summaries. Journal of Biomedical Informatics, 99, Article 103310.

[16] Kilintzis, V., Chouvarda, I., Beredimas, N., Natsiavas, P., & Maglaveras, N. (2019). Supporting integrated care with a flexible data management framework built upon Linked Data, HL7 FHIR and ontologies. Journal of Biomedical Informatics, 94, Article 103179.

[17] Lehne, M., Sass, J., Essenwanger, A., Schepers, J., & Thun, S. (2019). Why digital medicine depends on interoperability. NPJ Digital Medicine, 2, Article 79.

[18] Pfaff, E. R., Champion, J., Bradford, R. L., Clark, M., Xu, H., Fecho, K., Krishnamurthy, A., Cox, S., Chute, C. G., Taylor, C. O., & Ahalt, S. (2019). Fast Healthcare Interoperability Resources (FHIR) as a meta model to integrate common data models: Development of a tool and quantitative validation study. JMIR Medical Informatics, 7(4), e15199.

[19] Saripalle, R., Runyan, C., & Russell, M. (2019). Using HL7 FHIR to achieve interoperability in patient health record. Journal of Biomedical Informatics, 94, Article 103188.

[20] Braunstein, M. L. (2018). Health informatics on FHIR: How HL7's new API is transforming healthcare. Springer.

[21] Clarke, J. M., Warren, L. R., Arora, S., Barahona, M., & Darzi, A. W. (2018). Guiding interoperable electronic health records through patient-sharing networks. NPJ Digital Medicine, 1, Article 65.

[22] Haug, P. J., Narus, S. P., Bledsoe, J., & Huff, S. (2018). Promoting national and international standards to build interoperable clinical applications. AMIA Annual Symposium Proceedings, 2018, 555–563.

[23] Min, L., Tian, Q., Lu, X., An, J., & Duan, H. (2018). An openEHR based approach to improve the semantic interoperability of clinical data registry. BMC Medical Informatics and Decision Making, 18(Suppl 1), Article 15.

[24] Houston, L., Probst, Y. C., & Martin, A. (2018). Assessing data quality and the variability of source data verification auditing methods in clinical research settings. Journal of Biomedical Informatics, 83, 25–32.

[25] Davuluri, P. N. (2020). Improving Data Quality and Lineage in Regulated Financial Data Platforms. Finance and Economics, 1(1), 1-14.

[26] Rajamani, S., Kayser, A., Emerson, E., & Solarz, S. (2018). Evaluation of data exchange process for interoperability and impact on electronic laboratory reporting quality to a state public health agency. Online Journal of Public Health Informatics, 10(2), e204.

[27] Ranade-Kharkar, P., Narus, S. P., Anderson, G. L., Conway, T., & Del Fiol, G. (2018). Data standards for interoperability of care team information to support care coordination of complex pediatric patients. Journal of Biomedical Informatics, 85, 1–9.

[28] Sadoughi, F., Nasiri, S., & Ahmadi, H. (2018). The impact of health information exchange on healthcare quality and cost-effectiveness: A systematic literature review. Computer Methods and Programs in Biomedicine, 161, 209–232.

[29] Bloomfield, R. A., Jr., Polo-Wood, F., Mandel, J. C., & Mandl, K. D. (2017). Opening the Duke electronic health record to apps: Implementing SMART on FHIR. International Journal of Medical Informatics, 99, 1–10.

[30] Segireddy, A. R. (2020). Cloud Migration Strategies for High-Volume Financial Messaging Systems.

[31] Boussadi, A., & Zapletal, E. (2017). A Fast Healthcare Interoperability Resources (FHIR) layer implemented over i2b2. BMC Medical Informatics and Decision Making, 17, Article 120.

[32] Plastiras, P., & O'Sullivan, D. M. (2017). Combining ontologies and open standards to derive a middle layer information model for interoperability of personal and electronic health records. Journal of Medical Systems, 41(12), Article 195.

[33] Reisman, M. (2017). EHRs: The challenge of making electronic data usable and interoperable. P&T, 42(9), 572–575.

[34] Roehrs, A., da Costa, C. A., da Rosa Righi, R., & de Oliveira, K. S. F. (2017). Personal health records: A systematic literature review. Journal of Medical Internet Research, 19(1), e13.

[35] Wu, R., Chaba, S., Sawlani, S., Chu, X., & Thirumuruganathan, S. (2020). ZeroER: Entity resolution using zero labeled examples. Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data, 1149–1164.