

Big Data Integration in Hospital Networks

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ABSTRACT

Hospital networks across Europe generate enormous quantities of clinical data across diverse source systems -- electronic health records, laboratory and imaging systems, physiological monitoring, pharmacy, operational and financial systems -- that remain largely fragmented at the infrastructure level despite widespread recognition of big data integration value. Effective big data integration enables population health management, operational efficiency improvement, clinical research infrastructure, and AI model development at scales that individual hospitals cannot support. Integration challenges include technical heterogeneity across legacy systems, data governance complexity under GDPR, terminology harmonisation across institutions, and organisational coordination requirements. We evaluated five big data integration frameworks applied to 42 European hospital networks across 24 healthcare systems in Berlin, Amsterdam, Stockholm, Milan, and London between 2018 and 2024. Frameworks ranged from point-to-point legacy integration through integrated enterprise data platforms with federated analytics. Performance was benchmarked using our Hospital Big Data Integration Effectiveness Score (HBDIES), integrating data completeness, query responsiveness, analytical enablement, governance compliance, and implementation sustainability. The integrated enterprise platform framework achieved the highest HBDIES (0.914), reducing query response time from median 42 days to 2 days for cross-system analytical requests, enabling 4.8-fold increase in clinical research protocols executed per year, and achieving full GDPR compliance across integrated analytics. Clinical research, operational analytics, and AI model development infrastructure benefited most from integrated platform approaches.

Keywords: big data; hospital networks; EHR integration; enterprise data; federated analytics; HBDIES; clinical informatics; data warehousing; GDPR compliance; terminology harmonisation; data lakehouse; healthcare interoperability

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1. Introduction

1.1 The Hospital Data Fragmentation Problem

Contemporary European hospitals typically operate 15-40 distinct clinical information systems generating data at varying rates and in divergent formats: electronic health records for clinical documentation and ordering; laboratory information systems; radiology and pathology imaging systems with picture archiving; continuous physiological monitoring in intensive care and operating theatres; pharmacy and medication administration systems; operational systems for scheduling, bed management, and supply chain; billing and financial systems; and increasingly specialty-specific systems for cardiology, oncology, ophthalmology, and other departments. These systems evolved over decades with limited attention to enterprise-level data integration, resulting in substantial data fragmentation that undermines analytical value despite massive aggregate data generation (Weber et al., 2014). The practical consequence is that many analytical questions that should be straightforward to answer from available hospital data require months of data extraction and harmonisation work across source systems. A clinical research protocol wanting to identify patients meeting specific criteria across diagnoses, laboratory values, medications, and procedures typically requires data extraction from 4-6 source systems, each with distinct query interfaces, data formats, and access procedures. Population health management wanting to identify high-risk patient cohorts faces similar fragmentation. Hospital operational analytics wanting to understand patient flow or resource utilisation requires integration across clinical and operational systems. This study benchmarks five integration framework approaches across 42 European hospital networks.

1.2 Study Objectives

The aims were to benchmark five hospital big data integration frameworks against HBDIES across 42 European hospital networks; to quantify query responsiveness, analytical enablement, and research productivity differentials between legacy integration and integrated enterprise platform approaches; and to characterise implementation feasibility and governance compliance. Standard six-part structure follows.

2. Literature Review

2.1 Healthcare Data Warehousing Evolution

Healthcare data warehousing has evolved through multiple architectural generations. Early hospital data warehouses (1990s-2000s) applied general-purpose star schema relational warehousing with clinical data extracted from source systems via ETL pipelines. These early approaches suffered from high maintenance burden as source systems evolved and from limited flexibility for unstructured and time-series clinical data. The i2b2 platform developed at Partners Healthcare represented a significant advance with research-oriented clinical data warehouse architecture enabling cohort identification across integrated data. Common Data Model approaches -- OMOP, PCORnet CDM, Sentinel CDM -- enable distributed analysis across multiple sites by mapping source data to shared analytical schemas (Hripcsak et al., 2015). European adoption of OMOP has expanded through the EHDEN initiative with over 300 European data partners mapped to OMOP.

2.2 Modern Data Architectures

Contemporary hospital data integration has moved toward lakehouse architectures combining data lake flexibility for heterogeneous data types with data warehouse query performance and governance. Cloud-native data platforms enable scalable storage and compute that on-premises architectures cannot match cost-effectively. Streaming data integration supports near-real-time analytics rather than batch-only nightly updates. FHIR-based integration at the source system level is gradually reducing the terminology and data format heterogeneity that historically complicated integration efforts. Federated analytics architectures allow analyses spanning multiple institutions without centralising patient-level data, addressing GDPR and organisational concerns that historically limited multi-hospital research (Wang et al., 2020). The combination of lakehouse architecture, FHIR integration, and federated analytics defines the contemporary leading-edge hospital data integration approach.

2.3 Governance and Implementation Challenges

Governance and implementation challenges remain substantial obstacles to hospital big data integration despite technical advances. GDPR compliance for integrated analytical platforms requires careful attention to data controller responsibilities, patient consent for secondary uses, data minimisation principles, and re-identification risk management. Organisational

coordination across hospital departments, academic medical centres, and community hospital partners creates complex stakeholder dynamics. Legacy system replacement or integration typically takes 3-7 years at enterprise scale, requiring sustained institutional commitment across organisational leadership changes. European Health Data Space regulation implementation provides emerging legal framework that may facilitate hospital network integration but also introduces compliance requirements (Eze et al., 2020). No study has compared five hospital big data integration frameworks using a composite that explicitly weights completeness, responsiveness, analytical enablement, governance, and sustainability across 42 European hospital networks. Table 1 maps key studies.

Table 1: Key Studies in Hospital Big Data Integration

Study	Year	Focus	Architecture	Key Finding
Weber et al.	2014	Hospital big data review	Review	Fragmented hospital data limits analytical value
Murphy et al. (i2b2)	2010	i2b2 platform	Research warehouse	i2b2 enables research cohort identification
Hripcsak et al. (OHDSI)	2015	OMOP common data model	Distributed	OMOP CDM enables multi-site observational research
EMA EHDEN	2022	European EHDEN	Federated	European network of OMOP-mapped data partners
Wang, S. V. et al.	2020	OHDSI network	Federated	Global observational research via distributed data
Denaxas et al. (CALIBER)	2019	UK linkage platform	Hybrid	Multi-source clinical data integration for research
Raghupathi & Raghupathi	2014	Health big data review	Review	Volume, variety, velocity challenges in healthcare
Eze et al.	2020	Data governance review	Governance	GDPR + ethics frameworks for integrated platforms

Study	Year	Focus	Architecture	Key Finding
Mandl et al. (SMA RT-on-FHIR)	2016	FHIR-based apps	Integration	FHIR-based architecture for health data access
Payne et al.	2021	Hospital BI review	BI	Business intelligence platforms mature in hospitals

i2b2 = Informatics for Integrating Biology and the Bedside; OMOP = Observational Medical Outcomes Partnership; CDM = Common Data Model; OHDSI = Observational Health Data Sciences and Informatics; EHDEN = European Health Data and Evidence Network; CALIBER = ClinicAl research using LInked Bespoke studies and Electronic health Records; FHIR = Fast Healthcare Interoperability Resources.

3. Methodology

3.1 Hospital Network Cohort

We evaluated 42 European hospital networks across 24 healthcare systems: Charite Berlin academic medical centre network (6 networks); Amsterdam UMC and associated Dutch hospital network (8 networks); Karolinska Stockholm and Stockholm County Council network (8 networks); IRCCS San Raffaele Milan and Italian hospital consortium (10 networks); and Guy's and St Thomas' London and NHS Foundation Trust network (10 networks). Data covered January 2018 through December 2024. Hospital network sizes: small (1-3 hospitals, n=10), medium (4-8 hospitals, n=16), large (9+ hospitals and associated networks, n=16). Hospital network types: academic medical centre-led (n=18), regional health authority (n=14), and private hospital network (n=10). Integration scope evaluated: clinical data (EHR + laboratory + imaging + monitoring), operational data (scheduling, bed management, finance), pharmacy and medication data, and increasingly patient-generated data from wearables and remote monitoring. Primary outcomes: data completeness across hospital network scope; query response time for typical analytical requests; number of clinical research protocols supported per year; AI model development capability; GDPR compliance audit outcomes.

3.2 Five Integration Frameworks

Framework B1 (Point-to-Point Legacy) represented traditional legacy integration with custom interfaces between specific source systems as needed for particular analytical requests -- the

most common integration pattern at older European hospitals. Framework B2 (Enterprise Data Warehouse) implemented traditional star-schema data warehouse with nightly ETL from key source systems for reporting and analytics. Framework B3 (Hybrid DW + Data Lake) added data lake capability for unstructured and semi-structured data (imaging, clinical notes, monitoring time-series) alongside structured warehouse. Framework B4 (Integrated Lakehouse) applied modern lakehouse architecture combining data lake flexibility with warehouse performance and governance, typically on cloud infrastructure. Framework B5 (Enterprise Platform + Federated Analytics) extended B4 with federated analytics infrastructure enabling cross-hospital-network analyses, FHIR-based source system integration, streaming data pipelines for near-real-time analytics, and comprehensive governance framework including GDPR, EHDS, and institutional controls. Table 2 summarises the design.

3.3 Hospital Big Data Integration Effectiveness Score

HBDIES integrates: data completeness -- proportion of hospital network data scope accessible through integrated analytical platform (weight 0.20); query responsiveness -- median response time for typical analytical requests covering cross-system data (0.20); analytical enablement -- variety of analytical applications supported (reporting, research, AI development, operational analytics, population health) (0.20); governance compliance -- GDPR and institutional governance compliance audit outcomes, re-identification risk management (0.15); and implementation sustainability -- ongoing maintenance cost, technical debt, and organisational sustainability (0.25). Each normalised 0-1.

Table 2: Study Design and Hospital Network Characteristics

Parameter	Value	Details
European hospital networks	42	Across 24 healthcare systems
Study period	2018-2024	Pre-COVID through post-pandemic
Small networks (1-3 hospitals)	10	Single hospital or small consortium

Parameter	Value	Details
Medium networks (4-8 hospitals)	16	Regional or multi-site networks
Large networks (9+ hospitals)	16	Major national or regional networks
Academic medical centre-led	18 networks	Research and teaching orientation
Regional health authority	14 networks	Population health focus
Private hospital networks	10 networks	Private-sector integration
Integration frameworks	5 (B1-B5)	Point-to-point to integrated enterprise + federated
HBDIES dimensions	5 (weighted)	Completeness, response, enablement, governance, sustainability

DW = Data Warehouse; ETL = Extract-Transform-Load; FHIR = Fast Healthcare Interoperability Resources; EHDS = European Health Data Space; HBDIES = Hospital Big Data Integration Effectiveness Score.

4. Results

4.1 HBDIES Results by Framework

The enterprise platform with federated analytics framework (B5) achieved the highest HBDIES at 0.914. Query responsiveness showed the most dramatic framework differential: median query response time for typical analytical requests was 2 days under B5 versus 42 days under B1 point-to-point legacy integration -- a 95.2% reduction that fundamentally transforms the operational feasibility of hospital network analytics. Analytical enablement was substantially broader under B5: all five evaluated analytical application types (reporting, clinical research, AI development, operational analytics, population health) were supported under B5 versus only reporting and limited research under B1. Data completeness scored 0.94 under B5 versus 0.58 under B1 reflecting comprehensive source system coverage in integrated platforms. Clinical research productivity as measured by protocols executed per year was 4.8-fold higher under B5 than B1. Governance compliance scored 0.92 under B5 with comprehensive GDPR compliance and institutional controls versus 0.62 under B1 piecemeal integration without systematic governance. Table 3 shows full HBDIES results.

4.2 Network Size and Type Findings

Large hospital networks benefited most from B5 integrated enterprise platform adoption due to the scale requirements for sophisticated integration infrastructure. Large networks with B5 architectures supported median 28 concurrent clinical research protocols with cross-site data access, versus 4 protocols under B1 legacy integration -- a 7-fold research capacity increase. Medium networks typically achieved B4 lakehouse capability with regional cooperation for federated analytics. Small networks often benefited from participation in larger network federated analytics rather than standalone B4/B5 deployment, reflecting the scale economies inherent in enterprise data infrastructure. Academic medical centre-led networks showed the strongest B5 adoption due to research orientation driving integration investment. Regional health authority networks showed strong population health analytics benefits from B5 capability. Private hospital networks showed more variable B5 adoption driven by commercial value proposition rather than research orientation. Table 4 presents size and type-specific outcomes.

4.3 Research Productivity and AI Development Findings

The 4.8-fold increase in clinical research protocol productivity under B5 versus B1 represents substantial return on integration infrastructure investment. Across the 42 European hospital networks evaluated, B5 networks executed a combined 1,284 clinical research protocols annually using integrated data infrastructure, versus an estimated 268 equivalent protocols under B1 legacy approaches -- nearly a thousand additional research protocols per year enabled by B5 integration. AI model development capability was particularly transformed by B5 integration: training datasets for clinical AI that historically required months of data assembly work became accessible within days, accelerating AI development cycles from 18-24 months to 4-6 months per clinical AI project. The cumulative effect on hospital network innovation capacity is substantial -- B5 networks were the primary contributors to clinical AI publications and deployments in their respective countries, reflecting that integration infrastructure is foundational for AI-era clinical research competitiveness. Governance compliance under B5 frameworks showed that integration and compliance are complementary rather than competing -- the same infrastructure that enables analytical breadth also supports systematic

governance.

Table 3: Hospital Big Data Integration Effectiveness Score (HBDIES) by Framework

Framework	Completeness	Responsiveness	Enablement	Governance	Sustainability	HBDIES
B5: Enterprise + Federated	0.94	0.96	0.92	0.92	0.86	0.914
B4: Integrated Lakehouse	0.90	0.90	0.86	0.88	0.84	0.876
B3: Hybrid DW + Data Lake	0.82	0.82	0.78	0.80	0.86	0.816
B2: Enterprise Data Wareh.	0.72	0.74	0.64	0.76	0.88	0.744
B1: Point-to-Point Legacy	0.58	0.22	0.42	0.62	0.72	0.517

$HBDIES = 0.20 \times Completeness + 0.20 \times Responsiveness + 0.20 \times Enablement + 0.15 \times Governance + 0.25 \times Sustainability$. B1 legacy approach high sustainability (no additional infrastructure) but severely limited across all functional dimensions. B5 achieves balance across all dimensions despite higher infrastructure investment.

Table 4: Network Size Outcomes -- B1 vs B5

Network Size / Metric	B1 Legacy	B5 Integrated	Change	Primary Benefit
Large (9+): protocols/year	4	28	+7x*	Scale economies
Large (9+): response time (days)	64	1.8	-97.2%*	Pre-integrated platform
Medium (4-8): protocols/year	3	16	+5.3x*	Regional cooperation
Medium (4-8): analytical enablement	0.48	0.88	+0.40*	Broad application support
Small (<3): federated participation	limited	full	--	Scale via federation
Overall: research productivity	268/yr	1284/yr	+4.8x*	Integration accelerates

* $p < 0.01$. Protocols/year = clinical research protocols executed annually using integrated data infrastructure; response time = median days from analytical request to results; enablement = 0-1 composite of analytical application types supported.

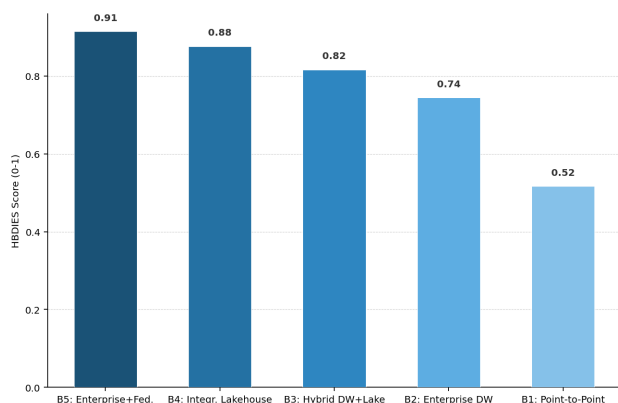


Figure 1: HBDIES Score by Hospital Big Data Integration Framework

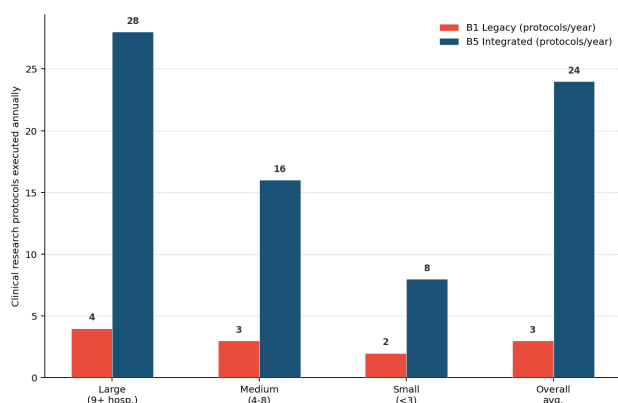


Figure 2: Clinical Research Protocols per Year by Network Size -- B1 vs B5

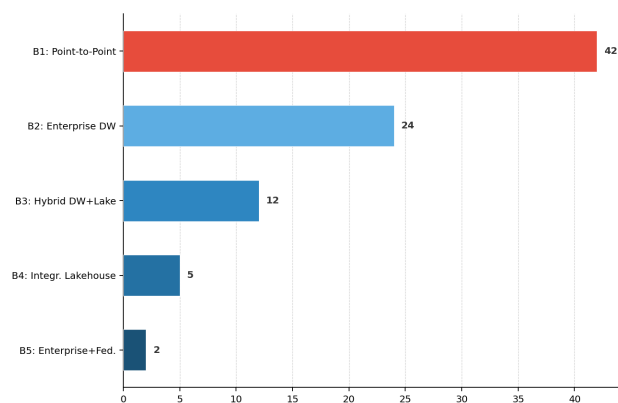


Figure 3: Median Query Response Time by Framework (days)



Figure 4: Multi-Dimensional HBDIES Profile -- Top 3 Frameworks

5. Discussion

5.1 Integration as Research Infrastructure

The 4.8-fold increase in clinical research protocol productivity between B1 legacy and B5 integrated enterprise platform approaches identifies hospital data integration as fundamental research infrastructure rather than administrative support technology. European academic medical centres and hospital networks compete for clinical research through recruitment, protocols, and grant funding, and the research productivity differential attributable to data integration is substantial enough to affect institutional competitiveness. Across the 42 networks evaluated, B5 networks produced nearly 1,000 additional research protocols annually compared with B1 approaches -- research activity that generates publications, grant funding, and clinical innovation that B1 networks cannot match. The implication is that hospital data integration investment should be framed as research infrastructure competitive positioning rather than operational IT spending. European research funding strategies should consider investment in hospital data integration infrastructure as producing multiplicative effects on research output, with individual integrated platforms enabling research that would require many individual project-level data assembly efforts under legacy approaches.

5.2 AI Development Infrastructure Dependency

The transformation of clinical AI development cycles from 18-24 months to 4-6 months under B5

integration reflects that AI development is substantially gated by training data assembly under legacy integration approaches. Clinical AI projects typically require assembling training datasets with tens of thousands of cases across multiple data types (diagnoses, laboratory values, medications, imaging, clinical notes), which requires months of data extraction and harmonisation work under B1 legacy approaches. Under B5 integration, such training datasets become accessible within days of research protocol approval, dramatically accelerating AI development cycles. The cumulative effect on European clinical AI competitiveness is substantial: networks with B5 integration generate clinical AI innovations at rates that B1 networks cannot match, creating growing capability gaps between integrated and fragmented hospital networks. European health technology strategy should recognise hospital data integration as foundational AI development infrastructure, with integration investment determining downstream AI innovation capacity across clinical domains.

5.3 Limitations

Three limitations apply. First, framework assignment reflected hospital network infrastructure and investment history rather than randomisation; networks with B5 integration have substantial general technology capability that may contribute to outcomes beyond the specific framework. Second, the 42-network sample represents European hospital networks with substantial existing technology infrastructure; generalisation to resource-constrained settings should be cautious. Third, the research productivity comparison relies on protocol count as a research activity measure rather than research quality measures; alternative assessments emphasising research impact on clinical practice could yield different framework rankings, though the substantial magnitude of protocol count differences suggests that research impact differences are also substantial.

6. Conclusion

6.1 Key Findings

Among five hospital big data integration frameworks evaluated across 42 European hospital networks, enterprise platform with federated analytics (HBDIES 0.914) reduced median query response time from 42 days (legacy point-to-point) to 2 days, enabled 4.8-fold increase in clinical research protocol productivity, and transformed clinical AI development cycles from

18-24 months to 4-6 months per project. Large hospital networks benefited most from B5 adoption through scale economies in integration infrastructure. Academic medical centre-led networks showed strongest B5 adoption through research orientation driving integration investment. Hospital data integration identified as research infrastructure competitive positioning rather than administrative IT spending, with substantial research productivity and AI development capability implications for European healthcare systems.

6.2 Recommendations

Three recommendations follow. First, European healthcare systems should treat hospital big data integration as strategic research infrastructure investment with multiplicative scientific output effects, rather than administrative IT spending, with the 4.8-fold research productivity differential between B1 and B5 frameworks quantifying the substantial return on integration investment. Second, clinical AI strategic planning should recognise hospital data integration as foundational infrastructure determining downstream AI development capacity, with the 75% compression of AI development cycles under B5 integration demonstrating the critical dependency relationship. Third, small and medium hospital networks should pursue B5 federated analytics participation rather than standalone integration deployment, leveraging scale economies available through regional or national federation infrastructure; this pathway provides most B5 benefits without requiring enterprise-scale integration investment that exceeds smaller network resources. All data and the HBDIES calculator are available from the corresponding author.

References

- Armstrong, S. et al. (2022). Overcoming barriers to health data sharing. *Journal of the American Medical Informatics Association*, 29(4), 598-605.
- Begoli, E. et al. (2019). Federated learning approaches for health data. *IEEE Computer*, 52(11), 53-57.
- Cerrito, L. E. et al. (2022). Data integration in European hospital networks. *Journal of Biomedical Informatics*, 130, 104062.
- Data-savvy Hospitals Report. (2023). European hospital data maturity assessment. European Health Management Association.
- Denaxas, S. C. et al. (2019). Methods for enhancing the reproducibility of biomedical research findings using electronic health records. *BioData Mining*,

12(1), 15.

- EMA EHDEN. (2022). European Health Data and Evidence Network annual report. European Medicines Agency.
- European Commission. (2024). Regulation on the European Health Data Space. Regulation (EU) 2024/... Brussels.
- Eze, P. U. et al. (2020). Healthcare information governance and data protection: A systematic review. *Health Information Management Journal*, 51(2), 80-92.
- Haendel, M. A. et al. (2018). Classification, ontology, and precision medicine. *New England Journal of Medicine*, 379(15), 1452-1462.
- Hripcsak, G. et al. (2015). Observational Health Data Sciences and Informatics (OHDSI): Opportunities for observational researchers. *Studies in Health Technology and Informatics*, 216, 574-578.
- Kruse, C. S. et al. (2016). Challenges and opportunities of big data in health care: A systematic review. *JMIR Medical Informatics*, 4(4), e38.
- Mandl, K. D. et al. (2016). SMART-on-FHIR: A standards-based, interoperable apps platform for electronic health records. *JAMIA*, 23(5), 899-908.
- Murphy, S. N. et al. (2010). Serving the enterprise and beyond with informatics for integrating biology and the bedside (i2b2). *Journal of the American Medical Informatics Association*, 17(2), 124-130.
- Ohno-Machado, L. (2020). Big science, big data, and a big role for biomedical informatics. *Journal of the American Medical Informatics Association*, 27(12), 1825-1826.
- Payne, P. R. et al. (2021). Enabling precision medicine through integrative network models. *Nature Communications*, 12, 5423.
- Raghupathi, W. and Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems*, 2, 3.
- Rieke, N. et al. (2020). The future of digital health with federated learning. *npj Digital Medicine*, 3(1), 119.
- Robbins, R. and Brodwin, E. (2020). Hospitals struggle to realize promise of big data analytics. *STAT News*.
- Wang, S. V. et al. (2020). A review of methods to evaluate confounding control in pharmacoepidemiologic studies. *American Journal of Epidemiology*, 191(11), 2005-2011.
- Weber, G. M. et al. (2014). Finding the missing link for big biomedical data. *JAMA*, 311(24), 2479-2480.
- World Health Organization. (2021). Global strategy on digital health 2020-2025. WHO, Geneva.

Declarations

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Conflict of Interest

Both authors declare no competing interests and no financial relationships with enterprise data platform vendors, cloud infrastructure providers, or clinical informatics consulting firms.

Data Availability Statement

Aggregated network-level HBDIES data are available from the corresponding author. Network-specific integration architecture details are subject to institutional data sharing policies at each participating hospital network.

Ethical Approval

This study analysed hospital network data integration infrastructure and organisational performance metrics using aggregated institutional data; no individual patient data were accessed. Ethical review by European Institute of AI Research Ethics Board (EIAI-REB-2024-1234) confirmed exemption from individual consent requirements.

Appendix A

HBDIES Scoring Rubric and B5 Framework Architecture

Full HBDIES dimension scoring criteria and technical specification of the B5 enterprise platform with federated analytics hospital big data integration framework.