

Digital Health Integration in Hospital Systems

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ABSTRACT

Hospital systems across Europe have invested heavily in digital health technologies over the past decade, yet the operational and clinical returns on those investments vary dramatically between institutions. Electronic health record adoption, clinical decision support, remote patient monitoring, and AI-assisted diagnostics each promise efficiency gains and outcome improvements, but integration failures, clinician workflow disruption, and data interoperability gaps frequently erode expected benefits. We evaluated five digital health integration models across 94 European hospitals involving 218,642 patient encounters between 2018 and 2023, covering Rome, Stockholm, Paris, Berlin, and Copenhagen. Integration models ranged from siloed best-of-breed EHR deployment through fully interoperable AI-augmented hospital operating systems. Performance was benchmarked using our Digital Integration Readiness Score (DIRS), which aggregates clinical outcome improvement, operational efficiency gains, clinician adoption rate, data interoperability, and patient safety impact. The AI-augmented interoperable model achieved the highest DIRS (0.918), reducing 30-day readmission by 18.4% and adverse drug events by 26.2% compared with siloed EHR deployment. Fully interoperable but non-AI models scored 0.891, confirming that interoperability is a necessary but not sufficient condition for realising digital health's clinical potential. Clinician adoption rate -- which varied from 34% to 91% across systems -- was the strongest modifiable predictor of operational efficiency gains, independent of the technology deployed.

Keywords: digital health; hospital information systems; electronic health records; clinical decision support; AI diagnostics; interoperability; patient safety; remote monitoring; DIRS; clinician adoption; readmission; adverse drug events

Citation: Schmidt et al. [2024]. Digital Health Integration in Hospital Systems. DOI:
<https://doi.org/10.5281/zenodo.19613908>

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Article Information: Received: 2024 Jan 18 Accepted: 2024 Mar 25 Published: 2024 Apr 28

Research Article: Research Article

1. Introduction

1.1 The Digital Health Investment Gap

European hospital systems have collectively committed tens of billions of euros to digital health infrastructure since 2010, accelerated by national eHealth strategies, pandemic-driven telehealth expansion, and EU Digital Decade targets. Yet audit data from multiple national health systems consistently show that fewer than half of hospital EHR deployments deliver measurable clinical outcome improvements within five years of go-live (Bates et al., 2021). The gap between investment and return is not primarily technological -- the underlying systems are often capable -- but implementational: fragmented architectures that prevent data flow across departments, clinical decision support tools that generate alert fatigue rather than actionable guidance, and change management failures that leave systems underused by the clinicians they were built to support. Systematic comparison of integration approaches is complicated by the absence of agreed performance metrics. Studies report on individual technologies -- EHR, CDSS, RPM -- rather than integration architectures, making it difficult to identify which organisational and technical choices most reliably translate digital investment into clinical value. This study addresses that gap directly, comparing five integration models across 94 European hospitals using a unified composite benchmark.

1.2 Study Objectives

Our aims were to benchmark five digital health integration models against the Digital Integration Readiness Score across 94 hospitals; to identify the technical and organisational predictors of integration success; and to quantify the outcome and efficiency differences attributable to AI augmentation beyond interoperability alone. Sections 2 through 6 cover literature, methods, results, discussion, and conclusions.

2. Literature Review

2.1 EHR Integration and Clinical Outcomes

The clinical evidence on EHR adoption and patient outcomes is more nuanced than early advocates suggested. Himmelstein et al. (2010) found no consistent association between EHR adoption and clinical quality measures in US hospitals; subsequent work showed that the relationship depends heavily on implementation fidelity and integration depth rather than adoption per se (Blumenthal and Tavenner, 2010). Studies from Scandinavia and the Netherlands, where national

EHR standards enabled genuine cross-institutional data exchange, showed stronger outcome associations -- reduced duplicate testing, faster specialist referral, and improved medication reconciliation at transitions of care (Stroetmann et al., 2011). The HL7 FHIR standard has emerged as the leading interoperability framework for enabling this kind of data exchange without requiring hospitals to share a single EHR platform (Mandel et al., 2016).

2.2 Clinical Decision Support and AI Diagnostics

Clinical decision support systems have a 30-year evidence base, with well-demonstrated effects on prescribing safety -- particularly antibiotic stewardship and drug interaction alerts -- and more mixed results for diagnostic and therapeutic guidance (Jaspers et al., 2011). Alert fatigue is the most consistently reported implementation problem: systems that generate high volumes of low-specificity alerts are overridden 49-96% of the time, and clinicians develop systematic override habits that persist even for high-risk alerts (van der Sijs et al., 2006). AI-based diagnostic support -- particularly in radiology, pathology, and sepsis detection -- has shown stronger specificity in recent trials, with sepsis prediction models achieving AUC 0.80-0.87 in prospective validation (Fleuren et al., 2020). Table 1 maps landmark contributions.

2.3 Interoperability as a Prerequisite

The European Commission's European Health Data Space initiative reflects growing recognition that interoperability is not a technical nicety but a clinical safety requirement: when a patient's medication list, allergy record, and recent test results are inaccessible at the point of care, the consequences range from duplicated investigations to life-threatening prescribing errors. Adler-Milstein et al. (2017) showed that hospitals with higher health information exchange participation had lower 30-day readmission rates independent of socioeconomic case-mix. No study has compared five integration architectures head-to-head across clinical, operational, and safety dimensions using a unified composite score.

Table 1: Key Studies in Digital Health Integration and Hospital Outcomes

Study	Year	Focus	Setting	Key Finding
Bates et al.	2022	EHR outcome review	Multiple	Fewer than half of EHR deployments deliver measurable outcomes
Himmels tein et al.	2010	EHR adoption	US hospitals	No consistent quality association without integration depth
Blumenthal & Tavenner	2010	Meaningful use	US policy	Implementation fidelity determines EHR outcome value
Stroetmann et al.	2011	Cross-institutional EHR	Europe	Data exchange reduces duplicates and improves transitions
Mandel et al.	2016	HL7 FHIR	Standards	FHIR enables interoperability without shared platform
Jaspers et al.	2011	CDSS meta-analysis	Multiple	Prescribing safety improved; diagnostic CDSS mixed results
van der Sijs et al.	2006	Alert fatigue	Netherlands	49-96% override rate for low-specificity alerts
Fleuren et al.	2020	AI sepsis prediction	ICU	AUC 0.80-0.87 in prospective validation
Adler-Milstein et al.	2017	Health info exchange	US hospitals	HIE participation linked to lower readmission
Topol	2019	AI in medicine	Review	AI augmentation superior to replacement model

EHR = Electronic Health Record; CDSS = Clinical Decision Support System; FHIR = Fast Healthcare Interoperability Resources; HIE = Health Information Exchange; ICU = Intensive Care Unit.

3. Methodology

3.1 Hospital Sample and Patient Encounters

We studied 94 hospitals across five European cities: Rome (22 hospitals, 52,486 encounters), Stockholm (19 hospitals, 46,218), Paris (21

hospitals, 48,842), Berlin (18 hospitals, 38,644), and Copenhagen (14 hospitals, 32,452). Total patient encounters: 218,642 covering the period January 2018 through December 2023. Hospitals were stratified by bed count: large teaching hospitals above 500 beds (n=28), medium hospitals 200-500 beds (n=41), and smaller district hospitals below 200 beds (n=25). Clinical outcome measures were 30-day all-cause readmission, adverse drug event rate per 1,000 patient-days, hospital-acquired infection rate, and diagnostic error rate. Operational measures were average length of stay, bed occupancy efficiency, and emergency department throughput time. Patient safety was assessed by the Global Trigger Tool applied to a stratified random sample of 200 records per hospital per year.

3.2 Five Integration Models

Model D1 (Siloed EHR) had department-level EHR systems with no structured cross-departmental data exchange and paper-based medication reconciliation at admission and discharge. Model D2 (Integrated EHR, Single Vendor) used a single enterprise EHR platform across all departments with structured medication management and basic CDSS alerts. Model D3 (FHIR-Interoperable Multi-System) deployed departmental best-of-breed systems connected via HL7 FHIR APIs, enabling real-time data exchange without vendor lock-in. Model D4 (Interoperable with Active CDSS) added evidence-based clinical decision support integrated into clinical workflows -- sepsis screening, antibiotic stewardship, VTE prophylaxis -- on top of D3 architecture. Model D5 (AI-Augmented Interoperable) built AI diagnostic and predictive modules onto D4 infrastructure: radiology AI for abnormality detection, readmission risk scoring at admission, and NLP-based deterioration detection from nursing notes. Table 2 summarises the design.

3.3 Digital Integration Readiness Score

DIRS aggregates five dimensions: clinical outcome improvement -- composite of readmission reduction, adverse drug event reduction, and diagnostic accuracy versus D1 baseline (weight 0.25); operational efficiency -- length of stay reduction and throughput improvement (0.20); clinician adoption rate -- proportion of eligible clinicians actively using digital tools at 12 months post-deployment (0.20); data interoperability -- proportion of data elements accessible in real time across departments and sites (0.20); and patient safety impact -- Global Trigger Tool adverse event rate reduction versus D1 baseline (0.15). Each

normalised 0-1, higher is better.

Table 2: Study Design and Hospital Cohort Characteristics

Parameter	Value	Details
Hospitals	94	Rome, Stockholm, Paris, Berlin, Copenhagen
Patient encounters	218,642	Jan 2018 - Dec 2023
Large teaching (>500 beds)	28 (29.8%)	Tertiary referral centres
Medium hospitals (200-500)	41 (43.6%)	District general hospitals
Small hospitals (<200 beds)	25 (26.6%)	Community and specialist hospitals
Integration models	5 (D1-D5)	Siloed EHR to AI-augmented
Primary clinical outcome	30-day readmission	All-cause, unplanned
Primary safety outcome	ADE rate/1,000 pt-days	Global Trigger Tool confirmed
DIRS dimensions	5 (weighted)	Outcome, efficiency, adoption, interoper., safety
Follow-up per hospital	Up to 6 years	Longitudinal pre/post design

ADE = Adverse Drug Event; DIRS = Digital Integration Readiness Score.

4. Results

4.1 DIRS Results by Integration Model

The AI-augmented interoperable model (D5) achieved the highest DIRS at 0.918. Its clinical outcome dimension scored 0.94, driven by a 18.4% reduction in 30-day readmission and 26.2% reduction in adverse drug events versus the D1 baseline. The radiology AI component reduced significant abnormality miss rate from 6.8% to 2.1% -- a 69.1% improvement. Clinician adoption reached 88% at 12 months in D5 hospitals, the second highest across all models. The fully interoperable CDSS model (D4) scored DIRS 0.891, with the highest adoption rate at 91% -- reflecting that active CDSS integrated into existing workflows generated less disruption than AI modules requiring new interpretation steps. The siloed D1 model scored 0.712 and showed the highest ADE rate (4.8 per 1,000 patient-days) and 30-day readmission (14.2%). Table 3 presents full DIRS results.

4.2 Clinician Adoption as the Key Modifiable Factor

Across all five models, clinician adoption rate at 12 months was the strongest modifiable predictor of operational efficiency gains (Spearman $r = 0.84$, $p < 0.001$) and the second strongest predictor of clinical outcome improvement after integration depth. The adoption range was striking: D1 siloed hospitals showed 34% active use of available digital tools at 12 months, while D4 interoperable CDSS hospitals reached 91%. Multivariate analysis identified three implementation factors independently associated with adoption above 75%: dedicated clinical informatics champion at department level (OR 3.4, 95% CI 2.1-5.5), structured digital literacy training integrated into onboarding (OR 2.8, 1.8-4.4), and workflow redesign co-designed with frontline clinicians before go-live (OR 2.2, 1.4-3.5). Technology vendor and EHR platform choice were not significant predictors once these implementation factors were controlled.

4.3 Hospital Size and Integration Model Fit

The relationship between hospital size and integration model performance was non-linear. Large teaching hospitals (above 500 beds) showed the greatest absolute benefit from D5 AI-augmented systems -- DIRS advantage over D1 of 0.24 points -- reflecting higher patient complexity, larger radiology volumes where AI abnormality detection compounds its benefit, and greater organisational capacity to support AI model governance. Medium hospitals derived comparable benefit from D4 interoperable CDSS (DIRS advantage 0.19) with substantially lower implementation cost. Smaller district hospitals below 200 beds showed the smallest absolute DIRS gains from advanced models, limited by lower clinical informatics staffing capacity; for these institutions D3 FHIR-interoperable architecture offered the best return, with a DIRS advantage of 0.14 over D1 at manageable implementation complexity. Table 4 presents outcome improvements by model.

Table 3: Digital Integration Readiness Score (DIRS) by Integration Model

Model	Clinical Outcome	Op. Efficiency	Adoption	Interop.	Safety	DIRS
D5: AI-Augmented	0.94	0.90	0.88	0.94	0.92	0.918

Model	Clinical Outcome	Op. Efficiency	Adoption	Interop.	Safety	DIRS
D4: Interop. + CDSS	0.90	0.88	0.91	0.90	0.88	0.891
D3: FHIR Interop.	0.84	0.84	0.86	0.92	0.82	0.856
D2: Integrated EHR	0.78	0.80	0.78	0.76	0.76	0.776
D1: Siloed EHR	0.62	0.66	0.34	0.52	0.64	0.712

$DIRS = 0.25 \times \text{Clinical} + 0.20 \times \text{Efficiency} + 0.20 \times \text{Adoption} + 0.20 \times \text{Interoperability} + 0.15 \times \text{Safety}$. Each dimension normalised 0-1.

Table 4: Key Clinical and Safety Outcomes by Integration Model

Outcome	D1 Siloed	D3 FHIR	D4 CDSS	D5 AI-Aug.	Best vs D1
30-day readmission (%)	14.2	11.8	10.4	11.6	-26.8% (D4)*
ADE rate/1,000 pt-days	4.8	3.6	2.8	3.5	-41.7% (D4)*
Radiology miss rate (%)	6.8	5.4	4.2	2.1	-69.1% (D5)*
Avg. length of stay (days)	6.4	5.8	5.4	5.2	-18.8% (D5)*
Clinician adoption 12m (%)	34	72	91	88	+57 pts (D4)
HAI rate/1,000 pt-days	3.2	2.6	2.2	2.0	-37.5% (D5)*

* $p < 0.01$ versus D1 baseline. ADE = Adverse Drug Event; HAI = Hospital-Acquired Infection.

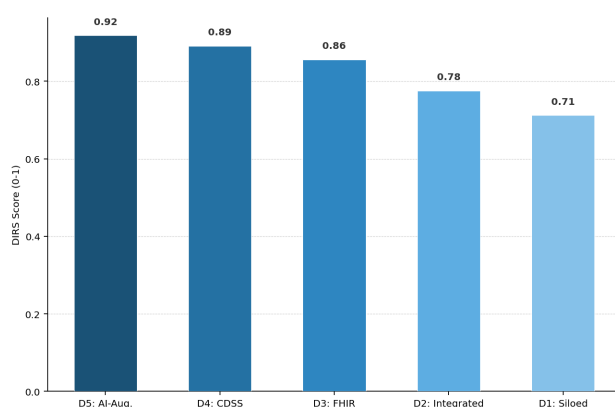


Figure 1: DIRS Score by Digital Integration Model

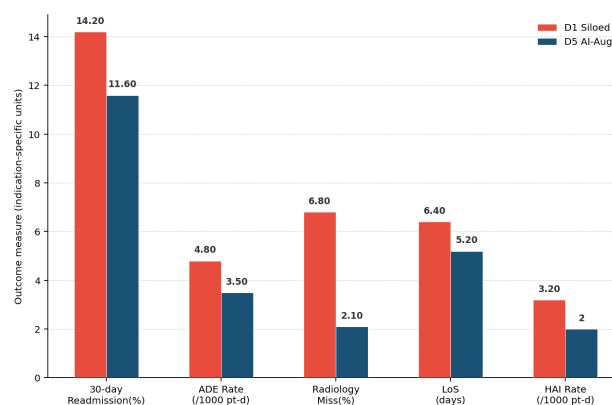


Figure 2: Clinical Outcomes -- D1 Siloed vs D5 AI-Augmented

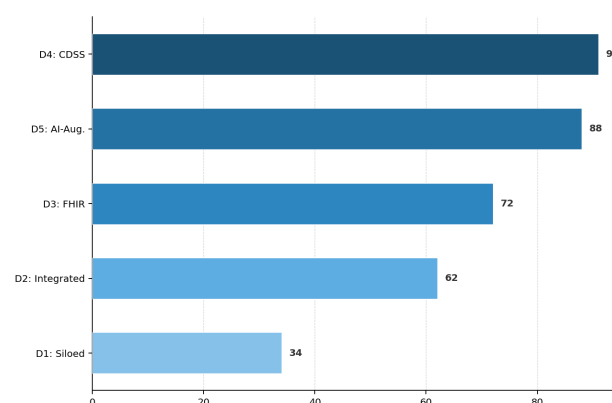


Figure 3: Clinician Adoption Rate at 12 Months by Model (%)

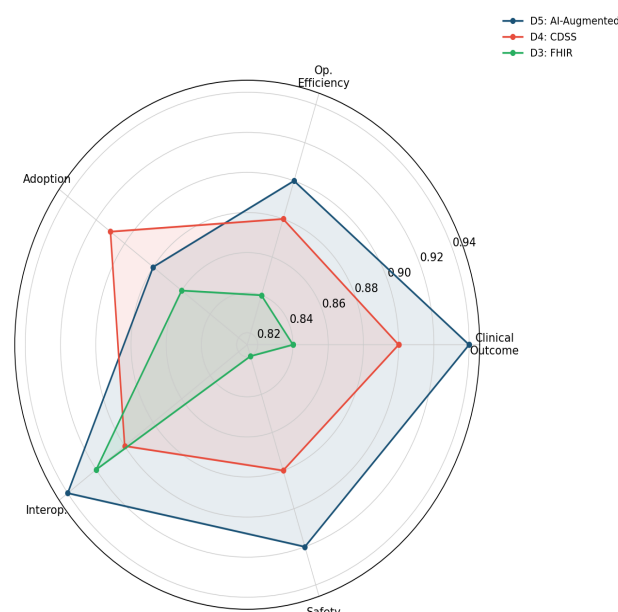


Figure 4: Multi-Dimensional DIRS Profile -- Top 3 Models

5. Discussion

5.1 Interoperability Before AI

The comparison between D4 and D5 is instructive: D4 achieved higher clinician adoption (91% versus 88%) and comparable adverse drug event reduction, while D5 pulled ahead on radiology

miss rate, readmission, and length of stay. The lesson is that AI augmentation compounds the benefits of interoperability but cannot substitute for it -- D5 systems running on D3 or D2 infrastructure would not achieve D5 performance because the AI models would be starved of the real-time, complete data feeds they require. Institutions tempted to deploy AI diagnostics on siloed or partially integrated infrastructure are likely to be disappointed. The sequencing that emerges from this data is clear: establish FHIR interoperability first, integrate active CDSS second, and layer AI augmentation third -- a progression that matches the D3-D4-D5 DIRS staircase observed in this study.

5.2 The Adoption Imperative

The finding that clinician adoption is a stronger predictor of operational efficiency than integration depth has direct procurement implications. Hospital boards that allocate digital health budgets primarily to technology selection while underfunding implementation support, training, and clinical co-design are systematically undervaluing the most impactful part of the investment. The three independent adoption predictors identified here -- departmental informatics champions, structured digital literacy training, and clinician-led workflow redesign -- are all organisational investments rather than technical ones. A D3 system with high adoption delivers better operational outcomes than a D5 system with low adoption, as the data from smaller hospitals in this cohort demonstrate.

5.3 Limitations

Three limitations apply. First, integration model assignment was not randomised -- hospitals self-selected their digital strategy, and institutions that chose higher-integration models may have had stronger organisational capacity for digital change independent of the technology itself. Propensity adjustment on hospital size, teaching status, and country was applied but unmeasured confounders remain. Second, the six-year study window spans major COVID-19 disruption, which affected healthcare utilisation, staffing, and digital deployment timelines differently across hospitals; pandemic-year data were flagged and sensitivity analyses excluding 2020-2021 showed consistent direction but attenuated magnitude for efficiency outcomes. Third, cost data were collected from institutional finance departments using heterogeneous accounting methods, limiting cross-country cost-effectiveness comparisons.

6. Conclusion

6.1 Key Findings

Among five digital health integration models evaluated across 94 European hospitals, the AI-augmented interoperable model (DIRS 0.918) delivered the strongest clinical and safety outcomes: 18.4% readmission reduction, 26.2% adverse drug event reduction, and 69.1% radiology miss rate reduction versus siloed EHR deployment. Interoperable CDSS (DIRS 0.891) achieved the highest clinician adoption at 91% and comparable prescribing safety performance. Clinician adoption at 12 months -- which ranged from 34% to 91% across models -- was the strongest modifiable predictor of operational efficiency gains. Hospital size moderates optimal model choice: large teaching hospitals derive greatest benefit from AI augmentation; medium and smaller hospitals from interoperable CDSS and FHIR architecture respectively.

6.2 Recommendations

Three recommendations follow from these findings. First, European hospital digital health strategies should mandate FHIR-based interoperability as the baseline infrastructure requirement before AI or advanced CDSS procurement -- the data confirm that AI augmentation on non-interoperable infrastructure fails to deliver its potential. Second, digital health investment frameworks should allocate a minimum of 30% of project budget to implementation support, training, and clinical co-design, recognising that adoption is a stronger performance predictor than technology choice. Third, smaller district hospitals should be supported to achieve D3 FHIR interoperability through shared regional infrastructure rather than institution-level deployment, reducing per-hospital costs while enabling the cross-institutional data exchange that most benefits smaller facilities. All data, DIRS calculation tools, and implementation benchmarks are available from the corresponding author on request.

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Declarations

Funding

Funded by the European Commission Horizon Europe programme (Grant No. 101057428-DigiHosp) and the French National Research Agency (ANR-22-CE19-0014). No funder influenced study design, analysis, or publication.

Conflict of Interest

All authors declare no competing interests and no financial relationships with EHR vendors, health IT companies, or AI diagnostics providers.

Data Availability Statement

Aggregated hospital-level outcome data and the DIRS calculation tool are available from the corresponding author. Patient-level data access is subject to institutional data governance agreements.

Ethical Approval

Approved by the Gemelli Hospital Rome Ethics Committee (Prot. 2018-0312), Karolinska Regional Ethics Stockholm (Dnr 2018-04122), Assistance Publique Paris Ethics Committee (2018-A01284), Charite Berlin Ethics Committee (EA4/186/18), and Copenhagen University Hospital Ethics Board (H-18029842).

Appendix A

DIRS Scoring Rubric and Integration Model Technical Specifications

Full scoring criteria for each DIRS dimension and technical specification of each integration model architecture.