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From Repeated Entry to Interoperability: A Synthetic Feasibility Study of Process Mining and FHIR R4 Redesign

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Abstract. Fragmented hospital applications may require the same demographic, clinical, and administrative information to be entered repeatedly across roles and systems. This synthetic feasibility study develops an auditable framework that links field-level occurrence classification and process-variant analysis to a provisional Clinical Data Redundancy Index (CDRI) and a Fast Healthcare Interoperability Resources (FHIR) R4 target architecture. A fixed-seed simulation generated 480 synthetic journeys across outpatient, emergency, medical check-up, and inpatient pathways, yielding 6,634 events and 96 complete-sequence variants. Repeated occurrences were classified as passive display, clinical confirmation, correction, or full re-entry; only correction and full re-entry entered the provisional CDRI calculation. Under the prespecified base scenario of 88% automation coverage and a 0.87 residual waiting-time factor, median manual-entry time decreased from 10.72 to 7.13 minutes (33.44%), while median journey time decreased from 250.73 to 233.45 minutes (6.89%). Simulated discrepancy opportunities decreased from 210 to 48 (77.14%). These values demonstrate the behavior of the proposed evaluation chain under stated assumptions; they are not estimates of hospital performance or clinical effectiveness. The methodological contribution is the integration of field lineage, process mining, provisional redundancy measurement, FHIR redesign, paired scenario analysis, and an explicit empirical-validation pathway. External calibration and prospective hospital validation are required before practical adoption.

Keywords: Electronic Health Record; FHIR R4; Process Mining; SATUSEHAT; Workflow Redesign.

1. INTRODUCTION

Electronic documentation supports continuity of care, billing, reporting, and quality improvement, but digitization does not automatically remove clerical work. Time-motion and event-log studies have shown that clinicians devote a substantial proportion of their working day to electronic health record (EHR) and desk activities (Sinsky et al., 2016; Arndt et al., 2017; Tai-Seale et al., 2017). Documentation burden is multidimensional and includes active entry time, after-hours work, workflow fragmentation, cognitive effort, and reduced patient interaction (Moy et al., 2021). These concerns are especially relevant when hospitals deploy several applications without a shared canonical data layer. In a fragmented architecture, registration, payer verification, nursing documentation, computerized physician order entry (CPOE), the laboratory information system (LIS), the radiology information system (RIS), pharmacy, billing, and health information exchange (HIE) may each request overlapping data. Re-entering identity, diagnoses, allergies, orders, and medication information consumes time and creates opportunities for transcription inconsistency. It can also propagate poor-quality source data or reproduce unsafe interface behavior (Weiskopf & Weng, 2013; Kahn et al., 2016; D'Amore et al., 2014; Koppel et al., 2005). Conventional satisfaction surveys cannot reliably identify the specific fields, handoffs, or variants in which avoidable full re-entry occurs. The novelty of this study does not lie in process mining, FHIR, or documentation-

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burden measurement considered separately. It lies in linking four analytical layers that are commonly treated independently: field-level lineage and occurrence classification; a time- and safety-weighted provisional redundancy metric; pathway and process-variant analysis; and a governed FHIR R4 redesign evaluated under paired and sensitivity scenarios. This linkage makes every modeled improvement traceable from a repeated field to the activity, pathway, target resource, reuse rule, and validation requirement that produced it. The contribution is therefore methodological and design oriented rather than evidence of clinical effectiveness. The work remains an explicitly synthetic feasibility study and does not evaluate the actual performance of the authors' hospital or any other institution. The study asked: (1) which data elements generate the greatest estimated full re-entry burden; (2) which synthetic pathways and variants have the highest provisional CDRI; (3) how can repeated fields be mapped to reusable FHIR R4 resources while preserving necessary confirmation and correction; and (4) how do the estimated operational effects change when automation coverage, safety weights, and waiting-time assumptions are varied? The prespecified analytical expectation was that single-entry, multiple-use data reuse would decrease manual-entry time more than total journey time because documentation is only one component of patient flow. No simulation-derived difference was interpreted as evidence of real-world effectiveness. Operational resilience was not measured: the simulation did not evaluate service continuity during outages, recovery time, data availability, or degradation under cyber or infrastructure disruption. For this reason, the revised title uses the more directly supported concept of interoperability rather than resilience.

2. THEORETICAL REVIEW

Documentation-burden research establishes that EHR time and desk work are measurable operational problems rather than anecdotal complaints (Sinsky et al., 2016; Arndt et al., 2017; Tai-Seale et al., 2017; Moy et al., 2021). EHR data-quality frameworks emphasize completeness, concordance, and traceability as prerequisites for reuse (Weiskopf & Weng, 2013; Kahn et al., 2016). At the same time, CPOE and data exchange can introduce new hazards when interfaces, terminology, or data ownership are not redesigned together (Koppel et al., 2005; D'Amore et al., 2014). Process mining offers a data-driven approach by reconstructing pathways from event logs rather than assuming that written procedures fully represent practice (Rojas et al., 2016; Munoz-Gama et al., 2022; van der Aalst, 2016; van der Aalst et al., 2012). Healthcare process mining can quantify variants, handoffs, loops, and bottlenecks, although clinical variability, parallel work, incomplete timestamps, privacy restrictions, and interacting data objects remain important challenges (Rojas et al., 2016; Munoz-Gama et al., 2022).

Reproducible Python libraries have improved accessibility (Berti et al., 2023; Maulana et al., 2026), but many studies stop at pathway description and do not connect field-level redundancy to a technically governed interoperability redesign. Fast Healthcare Interoperability Resources (FHIR) provides a modular, resource-oriented standard for exchanging health information through application programming interfaces (Lehne et al., 2019; Health Level Seven International, 2019; Ayaz et al., 2021; Mandel et al., 2016; Bender & Sartipi, 2013). Indonesia's SATUSEHAT platform uses FHIR R4 resources and use-case-specific implementation guidance (Ministry of Health of the Republic of Indonesia, n.d.). FHIR alone, however, does not guarantee less work: an interface may transfer duplication between screens unless identity resolution, terminology, source-of-truth rules, workflow ownership, provenance, exception handling, and human verification are redesigned together. Successful health information technology also depends on workflow fit, clinical ownership, iterative implementation, and organizational change (World Health Organization, 2021; Cresswell et al., 2013; Evans, 2016; Carayon et al., 2006).

The CDRI in this study is positioned as a provisional prioritization metric rather than a validated quality indicator. Existing documentation-burden studies quantify time and activity, while data-quality frameworks address completeness, concordance, and traceability; neither directly provides a field-level measure that links repeated capture to process variants and a target interoperability design. The provisional CDRI is intended to fill that design-stage gap. Its 1.25 safety multiplier for identity-critical, allergy, order, medication, and specimen-identity fields is an engineering assumption, not a clinical risk coefficient. Theoretical and empirical interpretation must therefore remain restrained until occurrence classification, timing, weighting, reliability, and construct validity are evaluated. The military-hospital context adds requirements for continuity, segmented infrastructure, role hierarchy, and sensitive personnel data, but the present simulation does not measure resilience and does not justify bypassing national standards.

3. RESEARCH METHOD

Study Design and Reporting Boundary

This was a simulation-based process-engineering study configured for an Indonesian military-hospital context. The workflow combined pathway generation, event-log construction, field-level classification, provisional CDRI calculation, directly-follows and variant analysis, FHIR R4 mapping, paired scenario evaluation, and sensitivity analysis. Figure 1 summarizes the analytical sequence. No patient record, staff-performance record, operational server log, or

identifiable military information was accessed. The simulation used random seed 20260731. Complete parameter files, synthetic event and field-lineage logs, case-level metrics, and executable Python code accompany the manuscript as supplementary materials. Consequently, the reported values are reproducible model outputs but must not be represented as empirical hospital measurements.

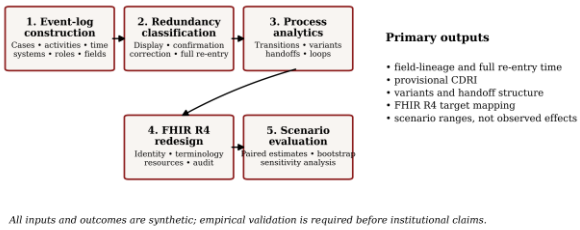

Figure 1. Analytical workflow for the synthetic feasibility study.

Synthetic Hospital Pathways

The simulation represented 480 end-to-end journeys: 180 outpatient, 120 emergency, 90 medical check-up, and 90 inpatient cases. Pathway branches were prespecified rather than estimated from hospital data. For example, the outpatient probabilities for payer verification, laboratory testing, radiology, and pharmacy were 0.80, 0.61, 0.24, and 0.76, respectively; the corresponding emergency probabilities for laboratory testing, radiology, pharmacy, and admission were 0.76, 0.43, 0.69, and 0.24. Inpatient length was sampled from one to four simulated days with probabilities 0.18, 0.38, 0.29, and 0.15. Table 1 reports the resulting pathway-level medians. The complete activity-time, field-entry, and remaining branch parameters are reported in the Appendix and supplementary parameter file.

Table 1. Profile of the fixed-seed synthetic dataset; all values are simulated medians unless otherwise stated.

Pathway	Journeys	Median events	Manual entry (min)	Full re-entry (min)	Median CDRI	As-is journey (min)	FHIR journey (min)
Outpatient	180	13	10.56	6.13	61.77	236.38	217.93
Emergency	120	12	10.16	6.00	62.16	247.45	230.12
Medical check-up	90	11	9.06	5.08	60.03	224.48	212.04
Inpatient	90	20	17.48	13.18	79.10	395.24	368.49

Simulation Parameters, Event-Log Structure, and Reproducibility

Each event contained a synthetic case identifier, pathway, event index, activity, timestamp, source system, role, field count, active entry time, full re-entry time, service time, waiting time, and paired FHIR-scenario estimates. Service and waiting times followed activity-specific gamma distributions. Field-entry durations followed log-normal distributions with $\sigma = 0.22$ and prespecified field medians of 3–25 seconds. Table 2 summarizes the simulation

controls; the exact activity and field parameters are reproduced in the Appendix and in simulation_parameters.json. The supplied analysis script regenerates all tables and figures from the same seed.

Table 2. Prespecified simulation parameters and reproducibility controls.

Seed and resampling	**Seed 20260731; 3,000 paired bootstrap resamples**	**Deterministic generator; case-level resampling**	**Intervals describe simulation sampling only**
Pathway counts	Outpatient 180; emergency 120; medical check-up 90; inpatient 90	Fixed totals; stochastic branches	Not derived from hospital case mix
Branch probabilities	Outpatient: payer .80, laboratory .61, radiology .24, pharmacy .76	Bernoulli branches; inpatient days categorical	Prespecified engineering assumptions
Service and waiting time	Activity-specific k and θ listed in the Appendix	Gamma(k, θ), minutes	Positive right-skewed durations
Field-entry duration	Median 3–25 s by field; σ = 0.22	Log-normal	No observed keystroke telemetry
Repeated occurrence modes	Identity .05/.20/.02/.73; clinical .05/.15/.03/.77	Display / confirmation / correction / full re-entry	Classification requires empirical inter-rater validation
CDRI weighting	Median entry time × 1.25 for safety-critical fields; alternatives 1.00 and 1.50	Weighted full-capture count	Multiplier is provisional, not validated
FHIR validation and automation	Validation = 2 s + 15% of original time; base automation 88%	Automated full re-entry becomes review; correction remains manual	Scenario estimate, not a deployed interface
Discrepancy probabilities	Identity .007; clinical .013; medication/order .020; other .009; automated reuse .0015	Bernoulli opportunity model	Not a clinical-error rate
Waiting adjustment	Eligible waiting × 0.87 in base; sensitivity 0.82–0.95; automation 0.60–0.95	Only events with automated repeated fields are eligible	Separates documentation and queue assumptions

Parameter Selection Rationale and Uncertainty Boundary

The simulation parameters were selected to test whether the proposed analytical chain behaves coherently under heterogeneous pathways, repeated-field patterns, and incomplete automation. They were not estimated from the authors' hospital. Fixed pathway totals ensured representation of four service settings, whereas stochastic branches created within-pathway variation. Gamma distributions were used for service and waiting times because those quantities are non-negative and commonly right-skewed; log-normal field-entry durations similarly prevented negative values while allowing occasional longer entries. Field medians were ordered by expected input complexity, with short coded attributes assigned lower values than narrative, order, and medication fields. These choices establish plausible engineering contrasts but do not constitute empirical calibration. Repeat-mode probabilities deliberately created a high-redundancy stress-test dataset so that field-lineage classification, pathway

ranking, and the FHIR reuse logic could be examined. The 88% automation coverage, 0.87 residual waiting-time factor, validation-time rule, discrepancy probabilities, and 1.25 safety multiplier were scenario parameters rather than observed rates. The sensitivity ranges were selected to include materially more conservative and more optimistic implementations. Accordingly, the base scenario is a reference configuration, not a forecast. Empirical use requires replacement of branch probabilities, field timings, occurrence modes, and automation performance with local estimates and should propagate parameter uncertainty through repeated-seed or probabilistic simulation rather than relying only on case resampling.

Clinical Data Redundancy Index

A repeated occurrence was classified before calculation as: (1) passive display, with no manual entry; (2) clinical confirmation, modeled as a brief review but not a new entry; (3) correction, requiring a human-authored replacement; or (4) full re-entry, requiring the field to be typed again. Only correction and full re-entry counted as repeated manual captures. This distinction prevents necessary review or passive display from being mislabeled as duplication. $CDRI(c) = 100 \times \Sigma[w(i) \times max\{m(i,c) - 1, 0\}] \div \Sigma[w(i) \times m(i,c)]$. Both summations are over all fields i. The term m(i,c) is the number of full manual captures of field i in synthetic case c, including the first capture and any subsequent correction or full re-entry. The weight w(i) equals the prespecified median entry time multiplied by 1.25 for identity-critical, allergy, order, medication, and specimen-identity fields, and by 1.00 otherwise. The 25% multiplier is an engineering assumption rather than a validated clinical risk coefficient. Sensitivity analyses therefore recalculated CDRI with multipliers of 1.00, 1.25, and 1.50. Empirical use would require observed timing, structured expert consensus, inter-rater testing of occurrence classification, and construct validation against staff burden and data-quality outcomes.

Planned Validation of the CDRI

CDRI validation is planned in four stages. First, content validity should be assessed by clinicians, nurses, medical-record personnel, pharmacists, laboratory and radiology staff, informaticians, and patient-safety experts to determine whether the field classes and weights represent meaningful burden and risk. Second, independent raters should classify passive display, confirmation, correction, and full re-entry in a sample of observed events; agreement should be reported with category-specific agreement and an appropriate chance-corrected coefficient. Third, criterion-related and convergent validity should compare CDRI with observed active-entry time, duplicate-field counts, correction workload, and staff-reported documentation burden. Fourth, responsiveness should be tested prospectively by evaluating whether CDRI changes in the expected direction after a defined interoperability intervention.

Correction and avoidable full re-entry should also be reported separately during validation because they represent different mechanisms. A correction can be a necessary safety action, whereas full re-entry may indicate avoidable duplication. The combined provisional CDRI is retained in this feasibility study to demonstrate the calculation, but future empirical analyses should provide component scores, uncertainty intervals, prespecified missing-data rules, and sensitivity to alternative timing and safety weights. No clinical threshold or acceptable CDRI range is proposed from the synthetic data.

Process Discovery and Variant Analysis

Directly-follows relations were calculated from adjacent activities within each case. Figure 2 displays the 18 strongest transitions, while all transitions remain available in the supplementary log. A process variant was the complete ordered activity sequence. Variants were ranked by frequency and cumulative coverage. The analysis is descriptive process mining and does not claim conformance to a prescriptive process model; no fitness, precision, or generalization score was inferred from the synthetic sequence generator.

FHIR-Based Redesign

The redesign applied a single-entry, multiple-use principle. Core FHIR R4 resources included Patient and RelatedPerson for identity context; Encounter, Location, Organization, and PractitionerRole for organizational context; Observation and DiagnosticReport for results; ServiceRequest and Specimen for diagnostic orders and specimens; Condition and AllergyIntolerance for clinical assertions; MedicationRequest, MedicationDispense, and MedicationAdministration for medication workflows; and Claim, Account, Task, Provenance, and AuditEvent for financial, workflow, and traceability functions (Health Level Seven International, 2019). Identifier was treated correctly as a FHIR data type used within resource elements, not as an independent resource. SATUSEHAT alignment was assessed at the level of the official FHIR R4 documentation and published resource catalogue (Ministry of Health of the Republic of Indonesia, n.d.). The target architecture is therefore described as SATUSEHAT-aligned, not as a validated SATUSEHAT implementation. Mandatory elements, terminology bindings, identifiers such as the Patient IHS number, canonical profiles, and transaction sequences remain use-case dependent and must be validated against the current implementation guide and sandbox before deployment. Local reuse rules were defined separately from national submission rules so that external interoperability would not create another internal re-entry step.

Table 3. Technical mapping of repeated data domains to FHIR R4 and SATUSEHAT-aligned implementation considerations.

Domain	Core FHIR R4 resource(s)	Data type / profile distinction	SATUSEHAT-aligned status	Local governance rule
Identity	Patient; RelatedPerson	Identifier is a data type within resource elements	Patient is a prerequisite; IHS number follows current guidance	Resolve once; governed correction; downstream reuse
Actors and location	Organization; Practitioner; PractitionerRole; Location	Resources may require current national identifiers and profiles	Prerequisite resources before clinical transactions	Role-based access and authoritative ownership
Encounter	Encounter; EpisodeOfCare	Use-case profiles determine cardinality and coding	Supported according to service-module guidance	One encounter identifier across subsystems
Clinical context	Condition; AllergyIntolerance; ClinicalImpression	Terminology and author/verification metadata remain mandatory	Use-case dependent supported resources	Reuse context; new assertion requires author and time
Diagnostics	ServiceRequest; Specimen; Observation; DiagnosticReport	Identifiers link order, accession, result, and correction	Supported in relevant diagnostic use cases	Order once; version corrections; monitor failed messages
Medication	MedicationRequest; MedicationDispense; MedicationAdministration	Medication coding and status rules are profile dependent	Supported in medication-related use cases	Prescriber/pharmacist validation; no demographic re-entry
Billing	Coverage; Claim; Account; Invoice	Resource support depends on transaction scope	Use-case dependent; verify current catalogue	Derive from documented services; exceptions reviewed
Audit and workflow	Task; Provenance; AuditEvent; OperationOutcome	Core FHIR resources; national support must be confirmed per profile	Task is documented; other use depends on current implementation	Attributable updates, retry queues, tamper-evident audit

Paired Scenario Model and Statistical Analysis

For each as-is event, the FHIR-enabled scenario retained the first capture. Passive display and clinical confirmation were unchanged; corrections remained human-authored. A full re-entry selected for automated reuse was replaced by a validation action equal to 2 seconds plus 15% of the original field-entry duration. Base automation coverage was 88%, modified by field class, and was varied from 60% to 95% in sensitivity analysis. For wait-eligible activities containing at least one automated repeated field, waiting time was multiplied by the residual waiting-time factor; all other waiting time was preserved. The base factor was 0.87 and was varied from 0.82 to 0.95. Continuous outcomes are reported as medians because the synthetic distributions were right-skewed. Paired effect estimates were summarized with 3,000 paired

bootstrap resamples of the 480 cases; the intervals quantify case-sampling variability within this simulation, not population uncertainty or clinical effectiveness. Wilcoxon tests and p-values were removed because inferential significance from deliberately generated paired data would be misleading. Model uncertainty was explored through the automation, waiting-time, and CDRI-weight sensitivity analyses. All analyses were performed in Python with pandas, NumPy, SciPy, matplotlib, and NetworkX.

4. RESULT AND DISCUSSION

Dataset and Process Complexity

The fixed-seed dataset contained 480 synthetic journeys and 6,634 events, with a median of 13 activities per journey. Ninety-six unique complete-sequence variants were generated. These values describe the simulation only and should not be interpreted as the case mix or workflow complexity of any real hospital.

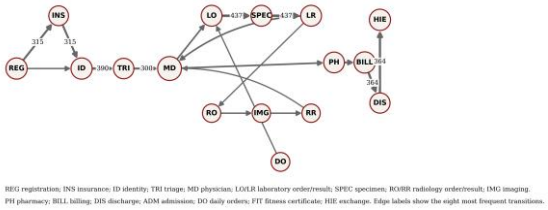

Figure 2. Directly-follows graph of the 18 strongest transitions in the synthetic event log. Node size reflects activity frequency and edge width reflects transition frequency.

The graph contains a common registration and identity trunk followed by divergent laboratory, radiology, medication, admission, billing, and discharge paths. Return transitions from results to physician assessment represent clinically meaningful reassessment rather than waste. The redesign target is the full re-entry embedded within necessary clinical pathways, not the removal of appropriate review, confirmation, or decision-making.

Field-Level Redundancy

Across all synthetic journeys, the median full re-entry time was 6.28 minutes per case and the aggregate full re-entry burden was 57.92 hours. The median case-level share of manual-entry time attributable to full re-entry was 58.88%. These values depend directly on the prespecified repeat-mode probabilities and must not be generalized to observed staff workload.

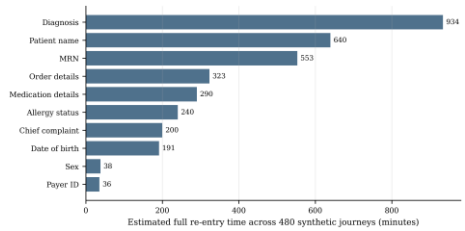

Figure 3. Data elements with the greatest estimated full re-entry time in the synthetic event log.

Table 4. Ten data elements with the highest estimated full re-entry burden; all values are synthetic.

Data element	Total occurrences	Full repeated captures	Repeat rate (%)	Estimated full re-entry time (min)
Diagnosis	4271	3012	70.5	933.8
Patient name	6634	4658	70.2	639.6
MRN	6634	4601	69.4	553.1
Order details	1427	843	59.1	323.1
Medication details	1175	667	56.8	290.2
Allergy status	1794	1153	64.3	240.4
Chief complaint	1194	583	48.8	199.9
Date of birth	2963	1851	62.5	191.4
Sex	1440	735	51.0	38.3
Payer ID	795	255	32.1	35.6

Diagnosis produced the largest estimated burden (933.8 minutes), followed by patient name (639.6 minutes), medical record number (MRN; 553.1 minutes), order details (323.1 minutes), and medication details (290.2 minutes). Identity fields occurred frequently, whereas diagnosis, order, and medication fields combined high frequency with longer prespecified entry times. The ranking is an output of the stated assumptions, not evidence that these fields are the dominant burden in the named hospital.

Clinical Data Redundancy Index by Pathway

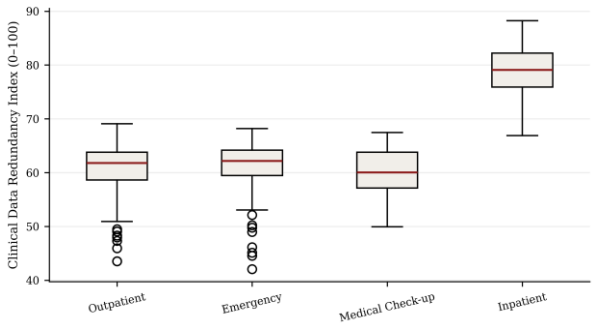

Figure 4. Distribution of the provisional CDRI by synthetic pathway under the 1.25 safety multiplier.

The overall median provisional CDRI was 62.80 with the base 1.25 multiplier. Pathway medians were 61.77 for outpatient, 62.16 for emergency, 60.03 for medical check-up, and 79.10 for inpatient journeys. Recalculation with multipliers of 1.00 and 1.50 produced overall medians of 61.48 and 64.00, respectively; case-level rankings were highly stable (Spearman $\rho \geq 0.997$), but the absolute score changed. This sensitivity confirms that CDRI should be presented as a provisional prioritization metric rather than a validated quality indicator. Among repeated occurrences, 74.85% were modeled as full re-entry, 17.80% as confirmation, 4.65% as passive display, and 2.70% as correction.

Process Variants and Redesign Coverage

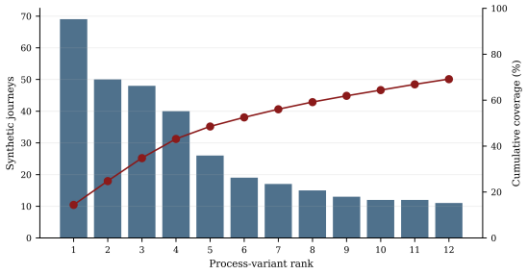

Figure 5. Pareto distribution of the 12 most frequent synthetic process variants.

Table 5. Eight most frequent synthetic process variants and cumulative coverage. Activity abbreviations are defined in Figure 2.

Rank	Abbreviated synthetic pathway	Frequency	Cumulative coverage (%)
1	Reg - Ins - ID - Tri - MD - LabOrd - Spec - LabRes - MD - Pharm - Bill - Disch - HIE	69	14.4
2	Reg - Ins - ID - Tri - LabOrd - Spec - LabRes - MD - FitCert - Bill - HIE	50	24.8
3	Reg - ID - Tri - MD - LabOrd - Spec - LabRes - MD - Pharm - Bill - Disch - HIE	48	34.8
4	Reg - Ins - ID - Tri - LabOrd - Spec - LabRes - RadOrd - Img - RadRes - MD - FitCert - Bill - HIE	40	43.1
5	Reg - Ins - ID - Tri - MD - Pharm - Bill - Disch - HIE	26	48.5
6	Reg - ID - Tri - MD - LabOrd - Spec - LabRes - RadOrd - Img - RadRes - MD - Pharm - Bill - Disch - HIE	19	52.5
7	Reg - Ins - ID - Tri - MD - LabOrd - Spec - LabRes - RadOrd - Img - RadRes - MD - Pharm - Bill - Disch - HIE	17	56.0
8	Reg - Ins - ID - Tri - MD - LabOrd - Spec - LabRes - MD - Bill - Disch - HIE	15	59.2

The 12 most frequent variants covered 69.17% of synthetic journeys, leaving a substantial long tail. The most frequent sequence accounted for 14.38%. A design limited to the dominant outpatient sequence would therefore fail to address many emergency, medical check-up, and inpatient variants. Resource-based reuse can support multiple orchestration

patterns without forcing every pathway into one rigid sequence (Lehne et al., 2019; Health Level Seven International, 2019; Ayaz et al., 2021; Mandel et al., 2016; Bender & Sartipi, 2013).

FHIR Target Architecture

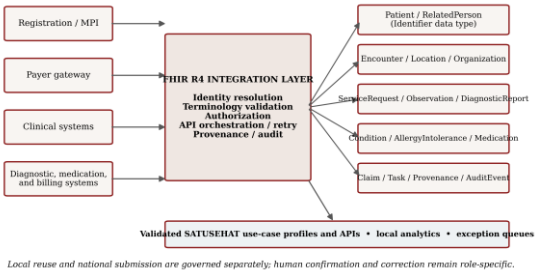

Figure 6. Conceptual FHIR R4 integration architecture for single-entry, multiple-use data reuse. MPI denotes master patient index. SATUSEHAT support and mandatory elements remain profile and use-case dependent.

The proposed architecture places identity resolution, terminology validation, authorization, retry queues, provenance, and audit in a governed integration layer between existing applications and reusable FHIR R4 resources. It is a conceptual target rather than a deployed interface. Legacy systems may initially operate through adapters, while authoritative identifiers and versioned resource updates are managed centrally. The architecture is SATUSEHAT-aligned because the same validated local resource layer can support use-case-specific national transactions (Ministry of Health of the Republic of Indonesia, n.d.). Alignment does not establish conformance. Patient IHS resolution, organizational prerequisites, mandatory fields, terminology, profile validation, authentication, and failed-transaction handling must be tested against the current SATUSEHAT implementation guide and sandbox. Internal order, specimen, result, medication, and billing identifiers should be linked before national reporting is used as a substitute for local integration. Security, data quality, and operational feasibility are central in a military-hospital context. The integration layer should enforce least privilege, network segmentation, encryption in transit and at rest, service-account rotation, tamper-evident audit, controlled pseudonymization, and tested downtime procedures. Implementation also requires master-patient-index governance, terminology services, resource versioning, idempotent transactions, retry and dead-letter queues, reconciliation dashboards, monitoring of duplicate resources, and explicit ownership of correction workflows. Automated reuse can propagate an incorrect source value at scale, while poorly designed CPOE or interface behavior may introduce new hazards (Weiskopf &

Weng, 2013; Kahn et al., 2016; D'Amore et al., 2014; Koppel et al., 2005). Human correction, provenance, reconciliation, exception handling, and safe manual fallback therefore remain mandatory.

Paired Operational Scenario

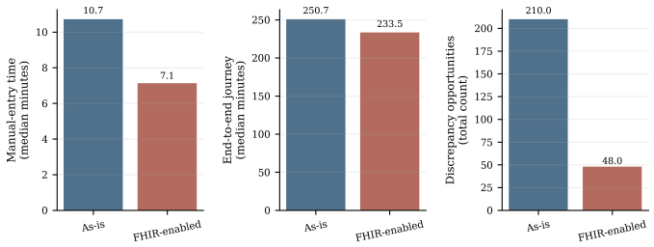

Figure 7. Base-scenario outputs in their original units. Values are simulation estimates rather than observed intervention effects.

Table 6. Paired synthetic outcomes under the prespecified base scenario.

Outcome	As-is	FHIR-enabled	Relative reduction	Interpretation / interval
Manual-entry time, median	10.72 min	7.13 min	33.44%	95% paired-bootstrap interval: 32.49%–34.14%
End-to-end journey time, median	250.73 min	233.45 min	6.89%	95% interval: 6.44%–8.45%
Aggregate time associated with repeated captures	57.92 h	24.96 h	56.91%	Automated reuse becomes brief validation; corrections remain manual
Discrepancy opportunities, total	210	48	77.14%	Prespecified probability model; not observed clinical errors

Under the base assumptions, median manual-entry time was estimated to decrease from 10.72 to 7.13 minutes, a 33.44% reduction (95% paired-bootstrap interval, 32.49%–34.14%). Median end-to-end journey time was estimated to decrease from 250.73 to 233.45 minutes, a 6.89% reduction (95% interval, 6.44%–8.45%). The smaller journey-time estimate is expected because laboratory processing, imaging, clinical decisions, bed availability, and non-documentation queues were largely preserved. Neither percentage represents an observed intervention effect. Simulated discrepancy opportunities decreased from 210 to 48, a 77.14% reduction. This is a risk-model output based on prespecified field-class probabilities. It is not evidence that FHIR prevents clinical errors, and it does not account for new interface-related failure modes or propagation of incorrect source data.

Sensitivity Analysis

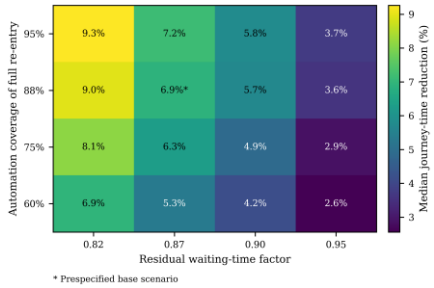

Figure 8. Sensitivity of the simulated median journey-time reduction to automation coverage and the residual waiting-time factor. The asterisk marks the base scenario.

Table 7. Selected simulation-sensitivity scenarios.

Conservative	**60%**	**0.95**	**2.56%**
Base	88%	0.87	6.89%
Optimistic	95%	0.82	9.26%

The median journey-time reduction ranged from 2.56% in the conservative scenario (60% automation; residual waiting factor 0.95) to 9.26% in the optimistic scenario (95%; 0.82). The base scenario was 6.89% (88%; 0.87), matching the abstract, narrative, Table 6, Table 7, and Figures 7–8. The gradient demonstrates that data reuse and queue assumptions interact; a real business case should report ranges and replace all assumptions with local observations.

Implementation Roadmap and Governance

A prospective implementation should proceed incrementally. Governance and baseline measurement should precede technical integration. Demographic and encounter reuse can be piloted first, followed by order–specimen–result linkage, medication reconciliation, billing derivation, and finally broader SATUSEHAT-aligned exchange. Process-mining dashboards should evaluate systems and pathways rather than rank individual staff unless a defined quality or safety purpose and appropriate governance exist.

Table 8. Concise phased roadmap for empirical validation and implementation.

0. Governance	**Legal basis, data inventory, threat model**	**Approved protocol and data owners**	**Authorized scope and minimum dataset**	**Pseudonymization; least privilege**
1. Baseline	De-identified logs plus direct observation	≥4–8 weeks; timestamp completeness; inter-rater agreement	Reliable field lineage and timing	No staff ranking
2. Identity pilot	Patient/Encounter identifiers and demographic reuse	Match accuracy, duplicate rate, time saved	Safe correction and merge workflow	Audit trail and manual override
3. Diagnostics	ServiceRequest–Specimen–Observation–DiagnosticReport linkage	Order–result linkage and failure recovery	Stable message and reconciliation rates	Retry queue and version control

4. Medication/billing	Medication workflow and coding derivation	Exception and discrepancy rates	Pharmacist/coder validation sustained	Human review of exceptions
5. Scale/exchange	Use-case profile validation and prospective evaluation	Staff, patient, safety, flow, and security outcomes	Sustained benefit without safety signal	Sandbox testing; downtime plan; audit

Implementation Feasibility and Real-World Evaluation

A real implementation should begin with a bounded use case rather than hospital-wide replacement. The identity and encounter pilot should document the authoritative source for each field, patient-matching and duplicate-resolution rules, local and national identifiers, consent and access constraints, terminology ownership, interface service levels, and rollback procedures. Legacy adapters should be tested for schema drift, delayed messages, duplicate submissions, version conflicts, and partial failure. Feasibility assessment should include development and maintenance cost, infrastructure capacity, licensing, training time, workflow disruption, help-desk demand, cybersecurity review, and the ability to operate safely during network or SATUSEHAT unavailability. Prospective evaluation should combine at least four to eight weeks of baseline measurement with post-implementation observation and, where feasible, a concurrent comparison pathway or phased rollout. Minimum outcomes should include active-entry time, full re-entry frequency, correction rate, patient-matching errors, failed and retried transactions, resource duplication, queue time, end-to-end journey time, staff workload and usability, safety events, downtime, and recovery performance. Analyses should be stratified by pathway and professional role, while dashboards should evaluate systems rather than rank individual staff. The simulated effect sizes should not be used for power calculations without local pilot estimates.

Relation to Prior Work

Prior documentation-burden research establishes the scale and multidimensional nature of EHR work, while healthcare process-mining studies reconstruct pathways, variants, and bottlenecks (Sinsky et al., 2016; Arndt et al., 2017; Tai-Seale et al., 2017; Moy et al., 2021; Rojas et al., 2016; Munoz-Gama et al., 2022). Those streams do not generally trace individual repeated fields from capture mode through pathway position to a governed target resource. The present framework contributes that traceability. Its novelty is the auditable linkage among occurrence type, field lineage, a provisional burden score, process variants, FHIR reuse rules, and scenario uncertainty. Because the event log is generated from prespecified pathways, the process-mining results demonstrate analytical feasibility rather than discovery of previously unknown hospital behavior. The FHIR contribution also differs from a stand-alone resource-mapping exercise. Prior work establishes FHIR as a technical basis for interoperable

applications (Lehne et al., 2019; Health Level Seven International, 2019; Ayaz et al., 2021; Mandel et al., 2016; Bender & Sartipi, 2013). This study links resource selection to the reason a field reappears and specifies when display, confirmation, human correction, or automated reuse is appropriate. The design therefore addresses workflow ownership and provenance in addition to message structure. Its contribution remains a target architecture and evaluation framework; it does not establish profile conformance, deployment feasibility, cost-effectiveness, safety, or resilience. Workflow fit, clinical ownership, iterative implementation, and organizational change are central to successful health information technology (World Health Organization, 2021; Cresswell et al., 2013; Evans, 2016; Carayon et al., 2006). In a military hospital, continuity requirements, segmented infrastructure, role hierarchy, and sensitive personnel data strengthen the need for granular authorization, minimum-necessary datasets, queued transactions, controlled local integration, and tested recovery procedures. These contextual requirements motivate the implementation roadmap, but they do not provide empirical evidence from a military hospital and should not be interpreted as demonstrated system resilience.

Limitations

The central limitation is that every numerical result is synthetic. Pathway probabilities, distributions, field lists, entry-time medians, occurrence classifications, CDRI weights, automation coverage, discrepancy probabilities, and waiting-time adjustments were prespecified for methodological demonstration rather than calibrated from hospital observations. The outputs therefore show internal behavior under stated assumptions and cannot estimate prevalence, workload, effect size, return on investment, or service improvement in a real institution. The paired bootstrap intervals quantify case-resampling variability within one generated dataset; they do not incorporate uncertainty in the input parameters, generator structure, or external population. Future simulation should use local probability distributions, repeated random seeds, and probabilistic sensitivity analysis. Second, the analysis uses a single case object even though real hospitals contain interacting patients, encounters, orders, specimens, medications, beds, invoices, and referrals. Object-centric process mining may represent those relations more faithfully (Berti et al., 2023). Because the event log was generated from prespecified pathways, the discovered variants partly recover the simulation design. Third, application timestamps do not necessarily equal active documentation time because idle periods, multitasking, copied text, and background processing can distort estimates. Prospective validation should combine de-identified logs with direct observation and privacy-preserving interface telemetry. Fourth, the FHIR scenario is not a

deployed intervention and does not model development cost, downtime, training, terminology maintenance, patient-matching failure, cybersecurity events, resource duplication, or unsafe propagation of source errors. Fifth, the combined CDRI currently groups correction with full re-entry even though they may represent necessary repair and avoidable duplication, respectively; its multiplier and occurrence classification have not undergone content, inter-rater, criterion, construct, or responsiveness validation. Finally, patient outcomes, staff experience, safety outcomes, equity, service availability, recovery time, and performance under disruption were not measured. Consequently, the study does not demonstrate operational resilience, and none of its outputs should support institutional claims before prospective validation.

5. CONCLUSION

This synthetic feasibility study presents a process-aware method for translating repeated clinical data entry into an interoperability redesign. Within the fixed-seed model, diagnosis, identity, order, and medication fields generated the largest estimated full re-entry burden, while inpatient pathways had the highest provisional CDRI. Under the prespecified base scenario, median manual-entry time decreased by 33.44% and median journey time by 6.89%. These values characterize the assumptions and generated event log only. The principal contribution is the auditable evaluation chain linking field lineage, occurrence classification, provisional redundancy measurement, process variants, FHIR R4 mapping, paired simulation, and sensitivity analysis. The study does not establish clinical effectiveness, generalizability, or resilience. Implementation should begin with governance, parameter calibration, and baseline measurement, followed by a bounded identity and encounter reuse pilot before expansion to diagnostic, medication, billing, and SATUSEHAT-aligned exchange. The CDRI should be validated through multidisciplinary content review, independent occurrence classification, comparison with observed time and burden measures, component reporting for correction and full re-entry, and prospective responsiveness testing. Real-world evaluation must also measure interface failure, data propagation risk, staff workload, safety, cost, availability, downtime, and recovery. Until those steps are completed, the framework should be interpreted only as a reproducible synthetic feasibility method.

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