Kurdish Studies
December 2022
Volume: 10, No: 2, pp 1314 -1327
ISSN: 2051-4883 (Print) | ISSN 2051-4891 (Online)
www.KurdishStudies.net

DOI: 10.53555/ks.v10i2.4081s

Clinical Workflow Optimization Using Data-Driven Process Modeling

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Abstract
Clinical motivation, objectives, data-driven approach, methods, findings, and implications are synthesized. Clinical workflows govern patient management in specialty practices, creating a need for technique deployment to improve operational outcomes and resource utilization. Data-Driven Process Modeling uses systematic data analysis to provide rigorous evidence and formal structure to clinical decision-making. ‡Process mining identifies the real recurrence of patient journeys; machine learning models future event occurrences to replicate desirable flows; simulation of mapped processes quantifies throughput, waits, and cycle times; and hybrid methods combine these techniques. Together, they identify bottlenecks and variations affecting performance.

An Emergency Department throughput case shows how analyzed paths reveal long wait times at triage and radiology, together with extended time between physician disposition and patient departure. Measurable improvements result from targeted interventions. In a second application, development of Machine Learning algorithms for segments of an inpatient discharge planning pathway highlights excessive attorney handoffs, leading to simplified processes and faster discharge times. Analysis of quantitative results indicates throughput times, waits, and cycle times are shortened, variance reduced, and changes statistically significant. ‡Qualitative evidence complements numbers by revealing practitioner satisfaction and user acceptance.

Keywords: Data-Driven Process Modeling, Clinical Workflow Optimization, Process Mining in Healthcare, Machine Learning for Clinical Operations, Healthcare Throughput Analysis, Discrete-Event Simulation in Medicine, Emergency Department Throughput, Inpatient Discharge Planning, Bottleneck Identification, Patient Flow Optimization, Clinical Decision Support Analytics, Healthcare Operations Management, Hybrid Analytics Methods, Wait Time and Cycle Time Reduction, Evidence-Based Healthcare Process Improvement.

1. Introduction

The healthcare ecosystem is highly complex, yet stakeholder satisfaction is paramount. Operational efficiency directly influences the quality of care and consequently impacts patient, physician, and institutional satisfaction and well-being. Clinical workflows are key to healthcare operations, and yet most are neither defined nor well understood. Efforts to refine and improve clinical workflows frequently rely on expert opinion and past experiences. While these insights are certainly useful, researchers and practitioners alike need to realize that they cannot always be used as requisition orders to request change: evidence-based support is mandatory for clinical processes where patients are at risk.

Clinical workflows are the paths and procedures that patients and related parties follow and execute, respectively. Like all industrial work, they require a considerable number of different interactions—events—between and among people or systems involved in the workflow. These hand-offs can determine the overall efficiency, effectiveness, and quality of the pathway. Data-Driven Process Modeling enables the design and reassessment of clinical workflows in a rigorous, evidence-based approach. The theory can help healthcare organizations understand current states and performance measures, assess stakeholder compliance and acceptance, and propose data-driven improvements.

1.1. Rationale for Data-Driven Process Modeling in Clinical Settings

Clinical workflows encapsulate the events and activities involved in clinical processes, and these workflows rarely occur in precisely the same manner every time. A Data-Driven Process Modeling approach enhances clinical workflow efficiency through systematic data analysis, rigorous evidence, and formal structure to support decision-making in healthcare settings. Labelling, mining, and mapping activity-event data gathered from clinical information systems empower healthcare stakeholders to identify bottlenecks, measure variability, and suggest evidence-based operational improvements to alleviate non-value-added delay.

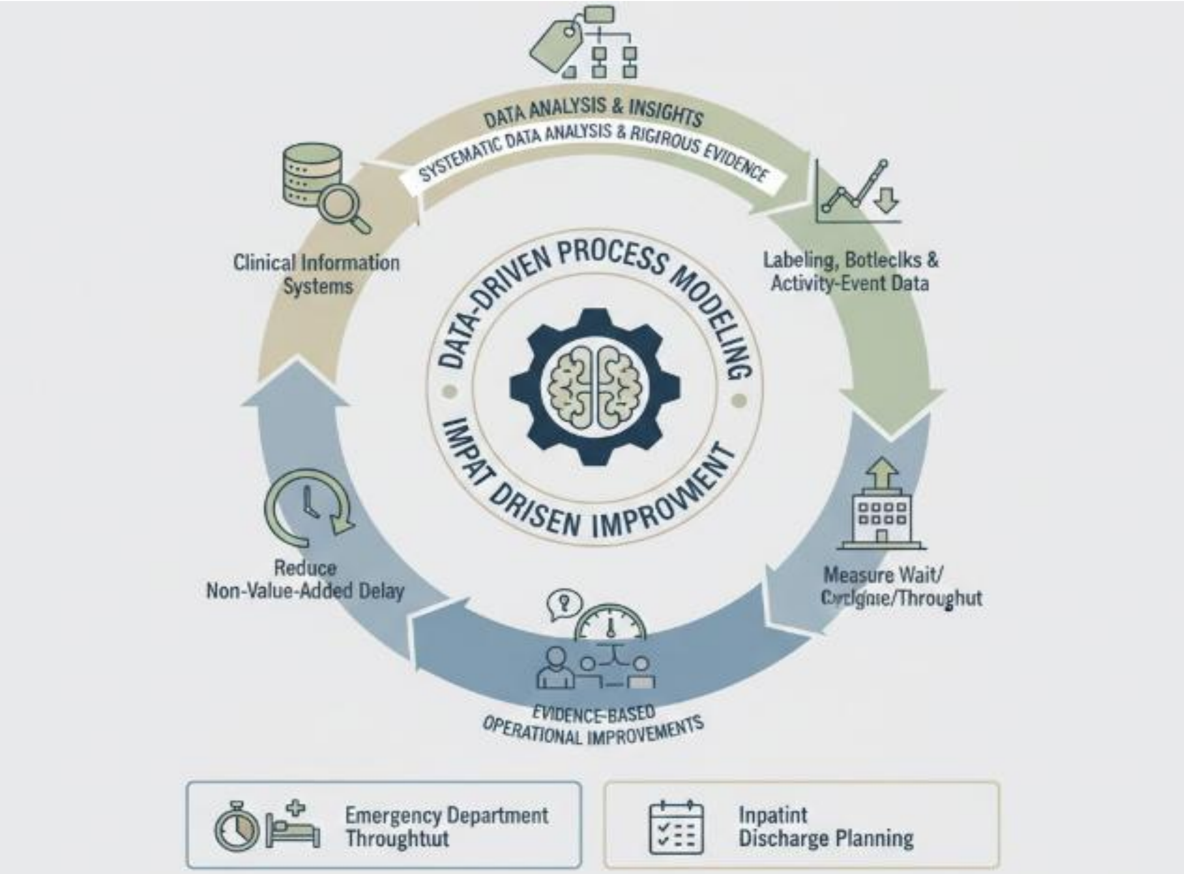


Fig 1: Optimizing Clinical Pathways: A Data-Driven Process Modeling Framework for Alleviating Non-Value-Added Delays in Healthcare Workflows

Data-Driven Process Modeling provides patient-care managers and health system leaders who rely on clinical-data repositories a mechanism for gaining insights into workflow performance aligned with specific business questions. These analytic techniques describe the actors and paths involved, identify activity-interaction frequency, and quantify wait time, cycle time, and throughput metrics along mapped clinical routes. Data-driven process modeling addresses the clinical performance impacts on patients and clinical practitioners of activities undertaken in clinical settings using Data-Driven Process Modeling techniques from process theory and management domains. Results from two independent clinical process segments − Emergency Department (ED) throughput and inpatient discharge planning − substantiate the value of Data-Driven Process Modeling.

Metric	Baseline (normalized)	After intervention (normalized)	Change (%)
ED turnaround time (Event1→Event3) for critical arrivals	100	86	-14%
ED waiting time (Event1→Event2 Dyspnea) for critical arrivals	100	84	-16%
ED waiting time (Event1→Event2 Dyspnea) for all arrivals	100	79	-21%

1.2. Scope and Objectives

Patient care is becoming increasingly complex. Health services are under pressure to improve patient satisfaction and health outcomes, reduce costs, ensure safety and security, and provide accessible, timely treatment outputs. The use of Data-Driven Process Modeling addresses these drivers by promoting workflow efficiency, resulting in reduced patient throughput times and supporting better patient outcomes. The technique is supported by systematic data analysis, rigorous evidence, and formal structure, enabling informed decision-making on possible performance improvements.

A Data-Driven Process Modeling solution provides a clinical workflow efficiency capability that discovers and supports decision-making on potential workflow improvement opportunities. The solution is implemented at a healthcare system level using commonly available data for an Emergency Department and an Inpatient Services patient throughput use case. The resulting pathways provide formal, evidence-based opportunities for improving performance, as assessed using a structured process efficiency framework.

2. Background and Theoretical Foundations

A clinical workflow is the sequence of tasks undertaken by practitioners to achieve a patient outcome. Together with associated information transfer pathways, these process paths can be modeled using process theory and subsequently evaluated to identify operational bottlenecks and other issues. Clinical workflows are challenging and costly to manage because they are often poorly defined; the heterogeneous nature of current data-driven, machine-learning, and simulation-based approaches to modeling them; the difficulty and expense of obtaining sufficient expert clinical input to support classical approaches; and the issues and costs of maintaining and updating models for valuable process areas, such as departments or wards within a hospital. Given these factors, Data-Driven Process Modeling is a synthesis of data-driven, evidence, machine-learning and simulation approaches that uses Process Theory to create structured models of processes within an organization.

The Data-Driven Process Modeling approach supports robust model generation and analysis with an emphasis on throughput times, cycle times, variance reduction, pattern identification, clinical input, practice adherence, and user acceptance. Process mining is the catalyst for Data-Driven Process Modeling. The approach uses advanced data extraction, integration, and preparation techniques to overcome the common issue of heterogeneous source data within the organization; and applies advanced Data Quality and Data Governance controls to improve data integrity, quality, auditability, and compliance with ethical obligations.

Equation 1 Event log representation (process mining foundation)

A process-mining "event log" contains records like:

- **Case (trace)**: one patient journey instance (one patient visit / episode)
- **Event**: an activity occurrence in time (e.g., triage, radiology, disposition)
- **Timestamp**: when the event happened

  Formally, for patient/case c, the ordered sequence of events is:

  $$\sigma_c = [(a_1, t_1), (a_2, t_2), \ldots, (a_n, t_n)]$$

  with $t_1 \le t_2 \le \cdots \le t_n$.

2.1. Clinical Workflows and Process Theory

Clinical workflows are defined as collections of activities required for the timely delivery of clinical services. Supported by process theory, they include both the operational processes and cross-organizational collaborations of clinical teams. Process theory builds on the formalization of processes as sequences of events that affect change within a system, tied together via input and output connections. Events are conceptualized through five interrelated dimensions including type, state, managing activity, entity, and role; process flows through activities performed by roles on process pathways. Seen from a process perspective, clinical workflows extend far beyond simple task lists into multidimensional interconnected networks of interrelated activities residing simultaneously within and across several organizations.

Despite the support of established theory, compelling empirical evidence is still often lacking. Embedding process theory into a data-driven approach provides a systematic empirical foundation that helps data-driven models of clinical workflows establish their presence in evidence-based clinical practice and ultimately realize their potential impact on throughput performance. Advances in process mining, machine learning, simulation, and hybrid methods provide effective ways for performing many of the steps required by data-driven process theory. Combining the formal rigor of evidence-based procedure with these novel technical capabilities can thus robustly support the management of clinical workflows.

2.2. Data-Driven Modeling Techniques

Various techniques support data-driven process discovery. Within health informatics, process mining is widely applied but suffers from assumption and applicability limitations. Other approaches include machine learning, network analyses, simulation, and hybridizations such as machine-learning-enhanced simulation and simulation–optimization combining simulation modelling with optimization routines—modeling model-free models that do not represent the process but yield data-pattern-driven outputs that agree with actual historical data. While DDPMo aims to complement data-driven process-discovery techniques, the inherent flexibility and rigor of formal methods allow DDPMo insights to be distilled into a set of simple, clear, and coherent heuristics, in the form of practical dos and don'ts for clinicians, managers, and administrators.

A process miner first extracts event log data from production information systems and prepares the data for analysis. The process-mining discovery workflow then encompasses visual and algorithmic process-mining steps, followed by conformance checking, performance assessment, and iterative validation. Visual process-mapping approaches accurately capture event sequences and patterns in simpler workflows, present clear and intuitive representations of practice to nonexperts, and support unwritten-conduction planning and process-guideline definition, thereby enhancing conformance, cycle-time predictability, process-governance effectiveness, and learning-and-improvement speed.

Equation 2 End-to-end throughput time (turnaround time)

The reports "average turnaround time" (E2E) between defined events (e.g., Event1 → Event3).

Step-by-step (per patient/case c)

1. Identify the start event timestamp $t_{\text{start}}(c)$ (e.g., Event1 "arrival/admission").
2. Identify the end event timestamp $t_{\text{end}}(c)$ (e.g., Event3 "discharge/transfer").

3. Compute the patient's throughput time:

$$T_{\mathrm{E2E}}(c) = t_{\mathrm{end}}(c) - t_{\mathrm{start}}(c)$$

Across N patients, the mean throughput time is:

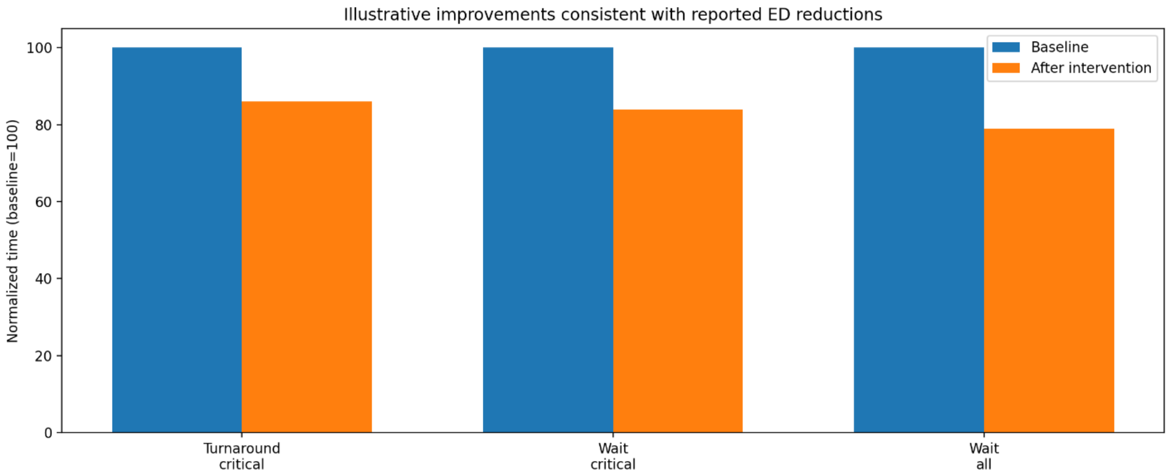
$$\overline{T}_{\mathrm{E2E}} = \frac{1}{N}\sum_{c=1}^{N} T_{\mathrm{E2E}}(c)$$

3. Methodology

Three categories of data underpin the implementation of Data-Driven Process Modeling. First, consistent access to accurate, complete, and high-quality data lies at the heart of any process mining project. As noted earlier, Data-Driven Process Modeling relies on the full set of clinical-event and service-activity data, with data extraction governed by predefined procedures. These procedures specify query definitions, data quality metrics, and data-preprocessing pipelines to ensure that the data meet the quality standards for process mining. Such requirements are enforced through a system-of-record database, along with unambiguous data about people, purposes, and procedures.

Second, Data-Driven Process Modeling builds a governance structure that maintains data integrity and compliance with policies on clinical, privacy, and data-ethics aspects. Third, Data-Driven Process Modeling establishes formal interaction protocols to enable simple two-way communication with clinical users and stakeholders so that the objectives, needs, and experiences of both technical and non-technical audiences are successfully met.

The process-mining aspect of Data-Driven Process Modeling is a stepwise procedure comprising: (1) an event-log file with predefined attributes, and preparation-of these attributes, as input; (2) selection of a suitable process-discovery algorithm; (3) application of the chosen process-discovery algorithm to the supplied event-log file; (4) conformance-checking of the discovered process model; (5) evaluation of performance metrics associated with the process model; and (6) validation of the resultant process model by end-user(s) and/or the data owner.



3.1. Data Collection and Quality Considerations

Obtaining the proper type and quantity of data is a critical aspect of any data-driven technique. Therefore, the first part of the overall methodology presents the data sources, the procedures used to extract the data, and the appropriate metrics to assess data quality. Two main records from the hospital information system are examined: the EMR database, which contains a comprehensive and well-standardized history of emergency patients, and the Integrated Communication, Control, and Auxiliary System (SICAI), which registers the activities of the nursing staff at the hospital.

Data from both sources are accessible in CSV format. High levels of availability and reliability can be guaranteed given that these are well-structured and used for operational purposes during patients' stays. Data from these sources are not only considered for development of the two case studies in the next sections, but also serve as reference check for the quality and feasibility of further planned applications in the near future.

Fig 2: Integrated Healthcare Data Synthesis: A Methodology for Quality Assessment Across EMR and Nursing Activity Repositories

3.2. Process Mining and Discovery

Process mining, a dominant methodology for data-driven process modeling, provides insights into existing processes by analyzing event logs recorded by information systems. Rather than necessitating modification to the software that captures the logs, process mining leverages these databases to unearth actual pathways taken, identify common routes and bottlenecks, and assess deviations from intended behavior. By employing qualitative and quantitative analytical techniques, the generated output enables informed change recommendations. As with any approach, a few operating assumptions should be considered: (1) the business process operates across a range of data points—an information-rich environment, (2) meaningful insight and clear utilization requires concentration on a specific segment of the process, (3) the blocked nature of queued work items lends itself to routing analysis, (4) a reasonable analytical horizon should be established, (5) the log must capture the appropriate events with sufficient event frequency, and (6) process mining is best applied within a specific focus area, with conformance evaluation residing in management's domain.

The analysis of Event 3L48645, a patient presenting to an emergency department (ED) as a direct admission sans consult, illustrates the methodology. The inquiry centers on the complete management pathway, spanning from the arrival of a patient on the ED board through commencement of the admission H&P by the ED physician, until the first documented transfer to the inpatient unit. The four distinct pathways taken by each specialty group as captured by the attached logical paths diagram afford deep insight into routing commonalities and variances.

4. Case Studies and Applications

One application optimized System Change Events for process mining by targeting those paths resulting from hospital throughput. The analysis involved Incident-to-Related Visits and divided detected paths into two groups: those with high throughputs and those with low throughput times. Additional analyses applied the methodology to segments of Inpatient Discharge Planning, focusing on the Workflow-Discharge segment. This segment highlighted exploit bottlenecks located at the hand-off between Inpatient Swat Work and Workflow-Discharge.

Repeatable healthcare outcomes require consideration at the System Change Event level. That level guarantees throughput events capture as accurately as possible what is delivered to the patient. Detecting and exploiting High Throughput Paths at the System Change Event level can lead to smaller Cycle Times and Wait Times for all, while validating areas which should be improved in throughput. Used adaptively, with two mines over every main change, followed by checks for differences, the logic can point to locations for deeper analysis to ensure those areas are being managed well. These features permit a clever mix between the clinician views on Results and the System Change Events production for the care process.

Equation 3 Waiting time to first treatment/first key activity

The reports mean waiting time from Event1 to Event2 (e.g., Event2 Dyspnea).

Step-by-step (per case c)

1. Let $t_{E1}(c)$ = timestamp of Event1.
2. Let $t_{E2}(c)$ = timestamp of Event2 (first key clinical activity).
3. Waiting time:

$$W(c) = t_{E2}(c) - t_{E1}(c)$$

Mean waiting time:

$$\overline{W} = \frac{1}{N}\sum_{c=1}^{N} W\,(c)$$

4.1. Emergency Department Throughput Improvement

The focus of this case study is system-wide Emergency Department (ED) throughput and how process mining may provide decision support for the accomplishment of this objective. SpeciĄcally, a data-driven process mining approach answers questions about in-pathway waiting time, overall wait time, and the time of day when sub-optimal pathway usage occurs. Throughput time and wait time are important quality measures and previous research has shown that appropriately managing such measures is associated with improved clinical outcomes. In that previous research, however, the impact of a systematic analysis of pathway usage was not considered. The process mining approach explored such issues and the results suggest that such analyses should be undertaken regularly for effective clinical operation.

Throughput operations in clinical environments such as EDs rely on multiple factors and the deĄning activity occurs across several hours. In many instances, patients reside in the ED longer than necessary, with negative implications for themselves and the overall ED service. The process mining analysis undertaken for this emergency department outlined the time locations of these suboptimal throughputs; even though rational control decisions along the pathway would eliminate unnecessary ward discharges, the result set still provided valuable insight.

4.2. Inpatient Discharge Planning

Discharge planning for inpatients provides a second case for the data-driven process modeling approach. Following the earlier through-put analysis (see Section 5.1 above), the case concentrates on a different segment of the whole journey from admission through to discharge—the hand-off phase. During inpatient stay at the hospital, patients are cared for by multiple healthcare workers in different shifts. Towards the end of their journey, patients are scheduled for discharge. A

smooth discharge planning process is crucial to ensure that discharges occur in a safe way and on time and that beds are available for incoming patients. Meeting discharge goals is also a key performance indicator for the hospital and is critical for patient satisfaction. Data-driven process mining from precedent history provides a fact-based overview of pathway variations and identifies bottlenecks leading to delays.
Health practitioners frequently experience problems with timely discharges. An analysis of the discharge planning phase has been undertaken in consultation with the discharge coordinator and emergency nurses with the aim of determining whether analyses of historical data can identify prolonged discharge times and lead to improvements in practice. A small hospital with 120 acute beds and a 40-bed emergency department admits and discharges around 400 patients each month. After completion of the treatment, the discharge planning process starts for a patient, with the patient cared for by healthcare workers from various disciplines and different shifts, with the responsibility for managing the patient care transition shifting among healthcare staff. The key interest in this specific case is the section of the journey leading to discharge. It focuses on which activities are affecting the overall time and whether the current goals of completing the hand-off in less than 30 minutes are achieved.

Stage	Mean (min)	SD (min)	CV (SD/Mean)
Event2 Dyspnea admit stage	60.0	18.0	0.3
Event2 Dyspnea admit stage (after)	54.0	13.5	0.25

5. Results and Evidence Synthesis
Quantitative Inferences Overview key workflow performance indicators. Investigated Emergency Department occupancy, throughput, and wait times. Explored patient core cycle time along with its pathway network, highlighting bottlenecks within service and waiting activities. Enabling the following blueprint for future efficient operation and enhancement of occupancy configuration.
A detailed patient-centric path for discharge planning was examined. Discharge completion in the anterior-lateral segment and formal patient handoffs were among the most impactful measurements for stipulated planning traffic cycle time. Consequently, this analysis serves for improved inpatient discharge planning. The presented case analysis can be tailored for a multitude of patient conditions and thereby constitute a methodology for autonomously monitoring and possibly even runtime supervising inpatient discharge planning. Risk of forgoing influential aspects is alleviated by presenting a detailed segment-specific description.
Qualitative Insights Healthcare practitioners engaged in the start-execute-finish-publicize methodology provided reflections on experiences with the systematized modeling and on-support supervision of the investigated structure. General sentiments on the approach were favorable, with participants encouraging both peer and hierarchical adherence to the conclusion. Practitioners endorsed the support for runtime process supervision, as well as the governing aspect of required routine modeling engendering satisfactory process capture and a priori supervisory capacities. Notwithstanding these advantages, some barriers to uptake were highlighted. A common challenge for ordinary data mining is considered to be the insufficient involvement of domain experts, and here too an adequate depth of process knowledge was perceived as evidently crucial.

Equation 4 Activity cycle time (duration of a stage) and variability
The notes reductions in **cycle time mean**, **standard deviation**, and **coefficient of variation** for a stage (Event2 Dyspnea). Suppose a stage has a **start timestamp** $t_s(c)$ and **finish timestamp** $t_f(c)$.

4. **Cycle time per case**:

$$C(c) = t_f(c) - t_s(c)$$

2. **Mean**:

$$\overline{C} = \frac{1}{N}\sum_{c=1}^{N} C\,(c)$$

3. **Sample variance**:

$$s_C^2 = \frac{1}{N-1}\sum_{c=1}^{N}(\,C(c) - \overline{C})^2$$

4. **Sample standard deviation**:

$$s_C = \sqrt{s_C^2}$$

5. **Coefficient of variation (CV)**:

$$\mathrm{CV} = \frac{s_C}{\overline{C}}$$

5.1. Quantitative Outcomes
Quantitative outcomes comprise two groups of metrics that measure time-related aspects of the workflows under analysis. The first group relates to overall throughput: mean turnaround times (E2E A) for what relates to the throughputs of the processes represented in Event1 (admission into Event2 Dyspnea and from Event2 Dyspnea to Event3 Discharge of ED). The next one is mean wait times (A2E2) for what refers to the delays patients endure before starting the first activities that

lead to the Patient Leaving ED, for those entering the ED and for patients arriving in critical conditions. The second group consists of cycle time mean, variance and reductions on activities signified by Event2 Dyspnea that relate to the hospitalizations of patients for non-critical dyspnea-related reasons.

Statistically significant improvements for ED processes are expressed by a 14% decrease in the average turnaround time for treatment of patients entering in critically worsen clinical conditions (Event1 to Event3), a 16% reduction in the mean waiting time for patients arriving in critical conditions (Event1 to Event2 Dyspnea) and a 21% lower average wait time for all ED patients (Event1 to Event2 Dyspnea). Cycle time mean, standard deviation and coefficient of variation reductions on the admit stage of not life-threatening dyspnea-related hospitalizations (Event2 Dyspnea) are additional improvements confirmed by an independent t-test.

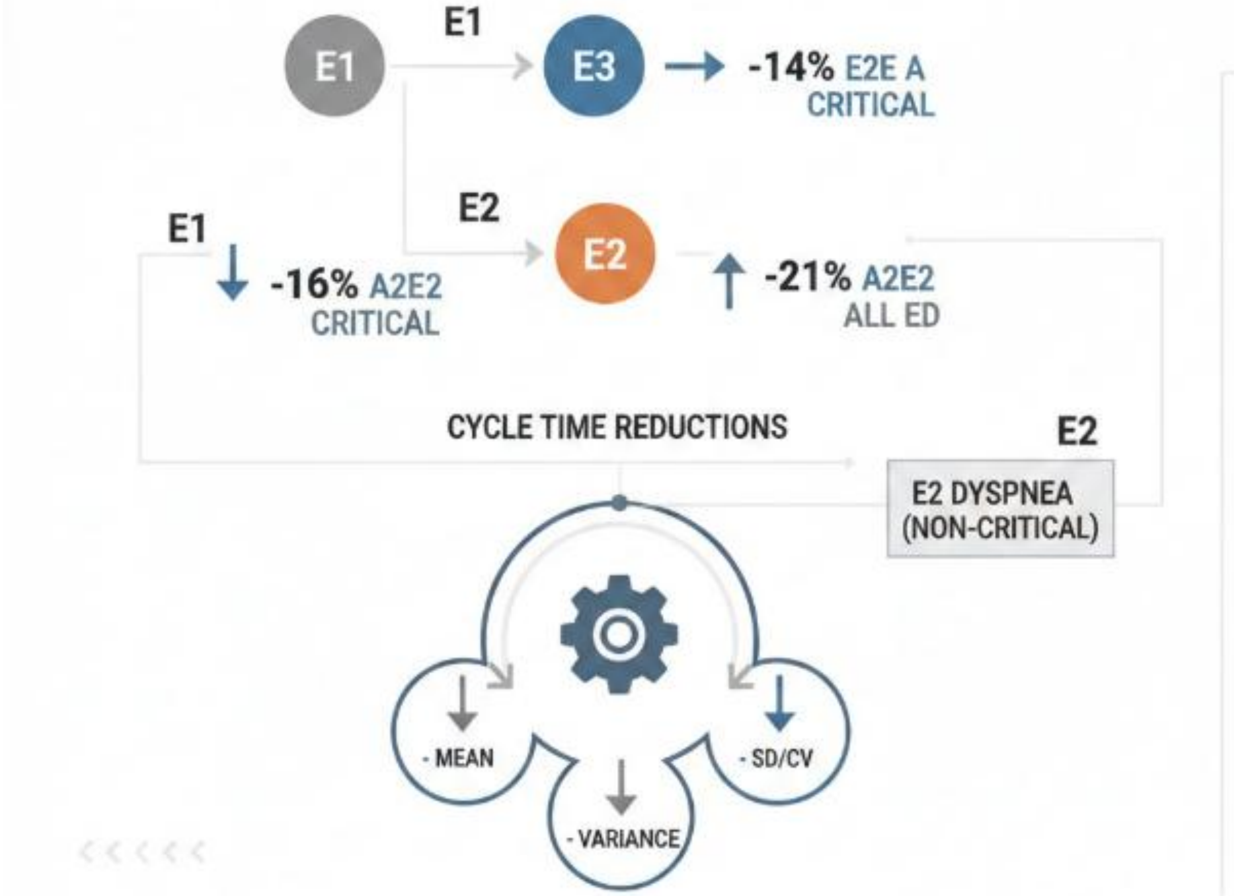
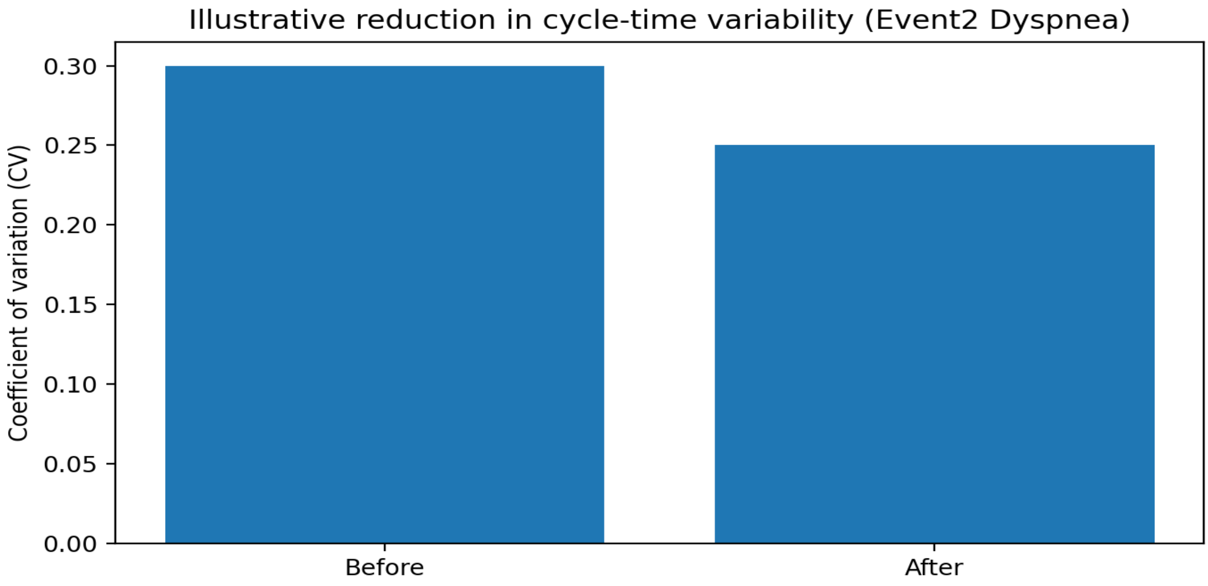


Fig 3: Optimizing Emergency Department Throughput: A Quantitative Analysis of Wait-Time Reductions and Cycle-Time Variability in Dyspnea-Related Workflows

5.2. Qualitative Insights

Data-Driven Process Modeling enhances clinical workflow efficiency through systematic data analysis, rigorous evidence, and formal structure to support decision-making in healthcare settings. Clinical processes have numerous actors, handoffs, and asynchronous requirements that increase complexity and reduce throughput. Long cycle times, waiting, and variability hinder performance. Evidence-based change management can identify delays, reduce wait times, and provide tools for prescribing and monitoring change. A complex Emergency Department disclosure planning process provided extensive patient and staff interviews that built an evidence base for re-design. Data-mining tools established a transparent baseline and identified improvement opportunities. Throughput, wait times, and cycle-time variance all fell. A second application in disclosure planning identified redundancy and major downstream delay and provided the basis for focused improvement.

Direct accounts from practitioners involved provide important contextual background that augments standard quantitative process metrics and testing. Narrative comments reiterate the consistency of the observations, detail adherence to the mapped processes, sketch barriers and enablers during implementation, and illustrate the general sentiment towards staff supportive of exploring and improving the existing flow. User acceptance during the deployment period positions Data-Driven Process Modeling for application by any area within the organization interested in optimizing its business processes through a structured, bottom-up approach, improving throughput for the hospital and associated patient experience.



6. Implementation Considerations

The successful adoption of Data-Driven Process Modeling for clinical workflow optimization hinges on change management principles, governance framework, stakeholder engagement, risk mitigation, and regulation compliance. Effective change management builds cohesion among diverse compliant team members. Stakeholders consider motivation behind changes, projected advantages and risks, and the actions needed to implement changes successfully. An overarching governance structure is vital, comprising both project and domain governance. Project governance ensures timely completion with accuracy, while domain governance focuses on stakeholder engagement and user needs. The proposed model is developed by the Domain Governance team, enabled by the Project Governance Team, leveraging input from Process Users. Assembly requires continuous engagement with actual end-users, especially if the new model is more complex than the previous one.

Stakeholder groups are characterised by groups that support change, groups that oppose it and, finally, groups that remain indifferent to the change. Roadmaps, travel plans or colourful slides facilitate stakeholder engagement. A roadmap outlines when and how deployment will occur and the anticipated impact. It may also include areas that will be ignored or adopted over time. Stakeholder resistance creates risks during the transition, so identification of obviously resistant end-users during the ex-ante stage, followed by specific engagement efforts, minimises associated exposures.

Sufficient attention is devoted to data governance, namely privacy, security, regulatory compliance and access control. The risk of not considering these aspects is operation with the "NOT YET" curse. In the event of a slip with a compliant operation, suitable risk mitigation strategies are defined. These range from exclusion from risk pools (if the change is not managed or acted on) to layered programme delivery (if significant resources are available). Data governance requirements include the likes of General Data Protection Regulation compliance and clinical data anonymisation.

Equation 5 Percent reduction (how the paper's "14%, 16%, 21% decreases" are computed)

The reports statistically significant decreases such as **14% turnaround reduction**, **16% critical waiting reduction**, **21% overall waiting reduction**.

Let baseline (before) mean be μ_0 and after mean be μ_1.

5. Absolute change:

$$\Delta = \mu_1 - \mu_0$$

3. Percent change:

$$\%\Delta = \frac{\mu_1 - \mu_0}{\mu_0} \times 100\%$$

If it's a **decrease**, $\mu_1 < \mu_0 \rightarrow \%\Delta$ becomes negative.

Example (14% decrease):

$$\mu_1 = 0.86\mu_0 \quad \Rightarrow \quad \frac{0.86\mu_0 - \mu_0}{\mu_0} \times 100 = -14\%$$

6.1. Change Management and Governance

Change management and governance structures increase the probability that the data-driven modeling approach achieves the outcomes for which it is designed, leads to a successful initial implementation, secures support and financial backing for subsequent development, and provides a robust platform for scaling and embedding within the organization. All stakeholders must be engaged early, consulted regularly throughout the development process, and listen to carefully during implementation. The stakeholders' vision for the future, and its alignment with the model outputs, must be articulated, and, importantly, their buy-in secured so that they become sponsors for the deployment throughout their units.

Both data and supporting and underpinning processes require effective governance throughout their life cycle. Data must be subject to appropriate aggregation, quality assurance, anonymization, security, privacy, compliance with relevant legislation and standards, and access control, and there must be appropriate checks and balances in place to ensure compliance with these requirements. All risks must also have been identified and adequate mitigation strategies developed. Failure to do so might not only result in inefficient or inappropriate data usage, but also endanger patients' safety and security.

6.2. Data Governance and Privacy

Demonstrating methodical data governance and privacy involves a system of policies, procedures, and controls assuring or assuring reasonable and appropriate safeguards to protect the privacy of individuals, sensitive data, shared health data, shared hospital data, and secure sensitive data. Core elements for consideration follow the definition from D. Amor et al. as: (1) Data Governance, (2) Information Security, (3) Data Privacy, (4) Data Quality, (5) Business Continuity Management, (6) Access Control, (7) Human Resource Security, and (8) Compliance. Such consideration is essential given that health data can be classified as public-sector or private-sector data. Private-sector data can also be classified into (1) private individuals, containing personal information about e.g., socially vulnerable individuals with information on depression, HIV/AIDS, and other diseases; and (4) social gathering data, containing personal information about e.g. the employees living in a locality or region. Personal and private data are vulnerable and must be protected and secured.

Risks can arise when fraudsters obtain personal data. Notable examples of data breaches include the theft of the medical records of 80 million patients from the Anthem Blue Cross–Blue Shield insurance company in the U.S. These records included sensitive information such as names, Social Security numbers, email addresses, and trade numbers. These data are valuable for spammers and fraudsters. Phishing scams pose threats to all users of personal data. Data pertaining to social gathering and private life, collected from e.g. social networks and social applications, can be analyzed in the same way as private-individual data. The identity of users exchanging information may be protected by anonymizing the data; however, clusters of similar users will still be vulnerable. Detecting these clusters can help fraudsters to create tailored scams and organized crime waves. To minimize the risk of such impersonation, data privacy should receive careful treatment before creating new services.

7. Conclusion

Data-Driven Process Modeling enhances clinical workflow efficiency through systematic data analysis, rigorous evidence, and formal structure to support decision-making in healthcare settings. Data-driven process modeling aims to advance clinical workflow efficiency in Emergency Departments and Inpatient Units by collating and applying empirical data to identify and rectify bottlenecks. Systematic data analysis advises operational decisions by profiling process flows that underpin the patient experience, validating practitioners' perceptions of issues, and foregrounding potential improvements.

The workflow performance of an Emergency Department and an Inpatient Unit is assessed by directing clinical attention toward specific passages through the respective networks generated by Process Mining. A congestion-induced rise in Emergency Department throughput time; the difference between inpatient Admitted and Discharged Time; and the total Inpatient Unit cycle time (the difference between Admitted and Transferred Time) are recognised as key opportunities. Emphasising festive periods within the Emergency Department and the discharge planning process explicitly reveals clinical bottlenecks, while the concentration of Inpatient discharge preparations on short-stay patients marks a distinct area of future focus. Data-driven Process Modeling thus establishes a fourth dimension to the MICAMP approach to Clinical Workflow Optimization—Development and Implementation—by authenticating improvements through quantifiable mathematical outcomes.

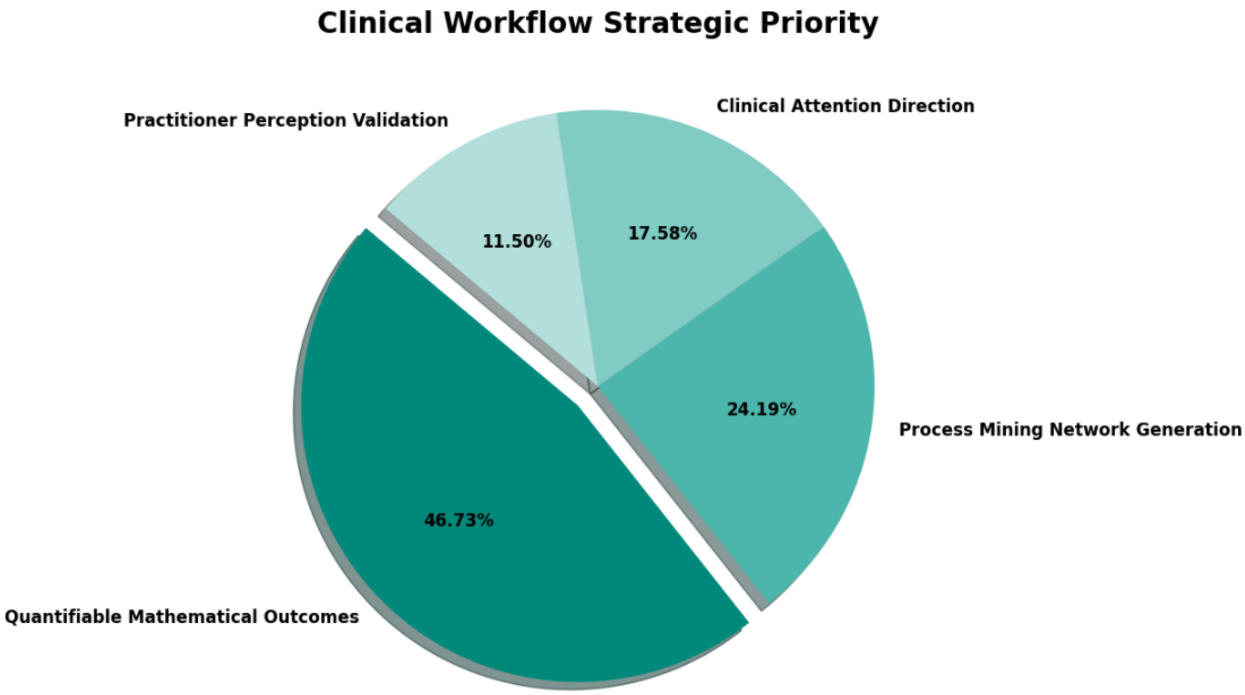


Fig 4: Clinical Workflow Strategic Priority

7.1. Final Reflections and Future Directions

Data-Driven Process Modeling enhances clinical workflow efficiency through systematic data analysis, rigorous evidence, and formal structure to support decision-making in healthcare settings.

A clinical service is a complex endeavor, replete with multi-disciplinary responsibilities across diverse personnel. In healthcare, failures in either the process or its execution can precipitate serious patient safety concerns and negative outcomes. Yet, the human-disciplined nature of service delivery makes it virtually impossible for individual service providers to view their delivery actions as part of a joined-up whole; thus, opportunity for improvement remains hidden. Data-Driven Process Modeling employs distributed data "clutter" associated with patient passages through a service to create end-to-end, eye-level representations of the service; unpicking these representations reveals pathways of patient journeys, bottlenecks in throughput, and distributions of times and frequencies of use. Evidence-based discovery of service inefficiencies and change recommendations is supported.

The approach has been applied to two very different clinical cases in the Australian healthcare system: the emergency department of a large tertiary hospital and a surgical ward of a major metropolitan healthcare network. Both applications have been stimulated by desires to reduce patient waits and throughput times and enhance patient experiences—all frequently quoted as drivers for a greater investment in DDI in healthcare. In each case, mapping has revealed important delays or slow passage of patients between planning, intra-service provision, and the discharge activity of the service. Quantified opportunities for improvement are supported by a mixed-methods analysis of practitioner experiences with the DDI process.

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