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A Surgical Process Mining Model to Improve Operational Efficiency in the Peruvian Healthcare System

Abstract*– Surgical backlog in low- and middle-income countries (LMICs) is exacerbated by fragmented information systems and weak process governance. Existing process mining solutions often assume data environments and governance maturity absent in LMIC public hospitals. We propose and evaluate a governance-integrated process mining framework architected for resource-constrained, digitally fragmented settings. The framework translates five inputs—clinical data, process definitions, infrastructure, controls, and policies—into actionable outputs through a four-layer architecture. A proof-of-concept in a Peruvian tertiary public hospital (1,234 surgical episodes, 2023–2024) revealed a critical 15-hour bottleneck between admission and preoperative preparation (IQR: 11–19), accounting for 62.5% of planned preoperative stay, and 39 distinct process variants indicating extreme pathway fragmentation. Conformance against the institutional protocol was 75% (fitness=0.75). Expert validation (n=15) rated integration of information between areas (4.81/5) and active participation of medical staff (4.75/5) as critical factors. However, a significant gap emerged between high perceived usefulness (4.50/5) and willingness to use (4.63/5) versus lower implementation feasibility (4.00/5) (p=0.010, Cohen's d=0.77). Reliability analysis yielded Cronbach's alpha of 0.89. This study provides a transferable, empirically grounded framework that moves beyond aggregate indicators to diagnose surgical inefficiencies, offering a roadmap aligned with national backlog reduction policies in LMICs.

Keywords-- Process Mining; Surgical Workflow; Low- and Middle-Income Countries; Healthcare Governance; Operational Efficiency; Perioperative Process; Event Log; Public Health Systems.

I. INTRODUCTION

Surgical care constitutes a fundamental pillar of health systems and a critical determinant of population well-being, particularly in middle-income countries where structural gaps and data fragmentation severely constrain timely and efficient service delivery. The Latin American Surgical Outcomes Study (LASOS)—a 7-day prospective cohort including 22,126 adult patients across 284 hospitals in 17 countries—revealed that 14.6% of surgical patients develop postoperative complications and 2.2% die during hospitalization, despite a predominantly low-risk profile [1]. The failure-to-rescue rate reached 15.1%, and a substantial proportion of deceased patients never accessed intensive care, evidencing deep-seated deficiencies in perioperative care organization and critical resource allocation [1]. In our case study, we identified that patients wait on average 15 hours between admission and preoperative preparation—equivalent to 62.5% of planned preoperative stay—a bottleneck invisible to traditional aggregate indicators.

Concurrently, regional evidence from Latin America underscores the magnitude of inefficiencies in surgical care delivery. Studies on surgical cancellations in Colombia report rates between 2.7% and 7.6%, with a substantial proportion attributable to administrative, logistical, and scheduling failures [2]. In Chile, a five-year analysis at a high-complexity hospital documented an 11.2% cancellation rate, with 80.1% of causes classified as preventable, leading to significant operating room idle time [3]. Brazilian data show cancellation rates reaching 15.55% in ambulatory surgery, predominantly due to patient non-attendance, unfavorable clinical conditions, and incomplete preoperative preparation, with over 90% of cancellations occurring on the day of surgery [4]. These patterns indicate that inefficiencies are not merely a consequence of insufficient installed capacity but also of weak process coordination, suboptimal operational control, and deficiencies in perioperative patient preparation. Such regional patterns are not isolated; they resonate strongly in Peru, where structural constraints amplify similar inefficiencies.

Peru exemplifies this reality. The Ministry of Health has explicitly recognized surgical backlog as a structural problem, implementing the "Surgical Backlog Reduction Plan 2024" which establishes ambitious targets for surgical output, prioritization of patients waiting over 60 days, and expansion of operating room hours [5]. Similar initiatives have been launched by the National Institute for Child Health and by EsSalud, the social security provider [6], [7]. These policy instruments define aggregate indicators—such as number of surgeries performed, cancellation rates, and operating room utilization—but do not specify methodologies for diagnosing underlying causes of inefficiency nor for systematically linking analytical findings to operational decisions on scheduling, prioritization, and resource allocation [5]–[7]. Prior work in the Peruvian context has demonstrated the feasibility of using process mining to evaluate operational variables in private hospital networks, revealing significant gaps between documented and observed processes [8]. Nonetheless, applications within the public sector remain limited, and literature offers few frameworks specifically tailored to resource-constrained, digitally fragmented settings.

Reliance on aggregate indicators alone obscures the real dynamics of perioperative processes. Avoidable cancellations, cumulative delays between activities, variability in patient trajectories, and bottlenecks in critical resources—such as recovery beds or supply availability—remain invisible to traditional management dashboards. This lack of analytical insight hinders the design of targeted interventions and sustains recurring inefficiencies, which, as regional evidence indicates, can only be addressed through diagnostic approaches at the process level.

In this context, process mining emerges as a powerful methodology for reconstructing actual surgical workflows from event logs within hospital information systems. By employing discovery techniques, conformance verification, and performance analysis, it becomes possible to detect inefficiencies, quantify deviations between planned and observed practices, and generate structured evidence to support protocol redesign and resource optimization. Recent developments in surgical research have further enhanced this approach through innovations such as machine learning integration, interactive visualization, and probabilistic modeling, all of which are examined in the following literature review.

However, the literature still lacks integrated models that explicitly articulate technological architecture, governance frameworks, and empirical validation in public health systems with structural constraints and limited digital maturity. Most proposals are validated in high-income settings or private networks, limiting their transferability to contexts such as Peru, where data fragmentation, skill gaps, and institutional resistance pose additional barriers. This article addresses that gap by designing and validating a surgical process mining model that integrates five essential components—clinical data, process definitions, technological infrastructure, operational controls, and information policies—within a governance framework explicitly designed for resource-constrained environments.

The main contributions of this work are threefold: (1) a conceptual and technological model articulating inputs and outputs in a structured manner, filling a recognized gap in the literature on process mining in middle-income health systems; (2) empirical validation through a case study in a Peruvian public hospital (1,234 surgical episodes) quantifying previously invisible inefficiencies—including a 15-hour bottleneck in the preoperative phase and 39 process variants—and demonstrating the approach's applicability in real-world contexts, extending prior Peruvian work from private to public sector settings [8]; and (3) a roadmap aligned with national surgical backlog policies, connecting analytical findings to operational decisions on scheduling, cancellation prevention, and resource optimization [5]–[7]. By embedding governance and feasibility considerations from the outset, the model offers a transferable framework for reducing surgical backlog and improving operational efficiency in comparable health systems across Latin America and other middle-income regions.

II. Literature Review

A. *Process Mining in Healthcare: Foundations and Evolution*

Process mining has emerged as a family of techniques bridging data science and process management, enabling the discovery, monitoring, and enhancement of real processes from event logs recorded in information systems [9]. In the healthcare domain, its adoption has grown exponentially over the past decade, as documented by comprehensive systematic reviews and tertiary studies [10], [11]. These works highlight the evolution from exploratory applications toward methodologically robust frameworks that address recurring challenges: heterogeneity of data sources, missing events, unreliable timestamps, and the imperative of explainability for clinical and managerial teams [12]. The healthcare context imposes demands—processes are highly variable, deeply dependent on human judgment, and subject to strict regulatory and ethical constraints—which have spurred the development of specialized guidelines for enhancing the usability and understandability of process mining outputs [12].

Recent tertiary reviews synthesize the state of the art across hundreds of studies, identifying dominant application areas (emergency care, chronic disease management, oncology pathways), prevalent techniques (inductive mining, fuzzy mining, conformance checking algorithms), and persistent gaps (data quality, governance, transferability to low-resource settings). In health technology assessment, process mining has demonstrated value in measuring process performance before and after introducing new technologies or organizational interventions, providing structured evidence for adoption and scaling decisions [13]. Case-mix planning and resource allocation have similarly benefited from event log analysis, enabling hospitals to understand patient mix, resource consumption patterns, and their impact on bed and operating room utilization [14]. Complementary approaches have integrated process mining with Lean Six Sigma methodologies to analyze hospital supply chain quality, demonstrating the potential of these synergies for simultaneously improving quality and efficiency [15].

B. *Perioperative Efficiency and Surgical Pathway Analysis*

The surgical process constitutes a complex care trajectory integrating preoperative, intraoperative, and postoperative phases, involving multiple clinical and administrative actors and depending critically on resources such as operating rooms, ICU beds, equipment, and supplies [16]. Systematic reviews of care pathway mapping demonstrate that small inefficiencies in activity coordination can escalate into extensive waiting lists, staff overload, and increased clinical risk [16]. Simulation models applied to orthopedic elective resource planning in England have shown that suboptimal scheduling decisions generate persistent bottlenecks and inefficient operating room utilization, with ripple effects throughout the surgical day [17]. Research on treatment delays in complex healthcare processes further confirms that understanding the temporal dynamics of care trajectories is essential for identifying intervention points [18].

The challenges documented across Latin American health systems—where preventable cancellations and delays are pervasive—highlight the urgent need for process-level diagnostic capabilities that can inform targeted interventions. Studies examining factors attributable to scheduled surgery cancellations have identified common patterns including incomplete preoperative preparation, insufficient resources, and coordination failures [19]. Understanding the root causes of these inefficiencies requires analytical approaches capable of capturing the dynamic complexity of perioperative workflows [20].

C. Surgical Process Mining: Advances and Applications

In recent years, a dedicated subset of studies has focused specifically on surgical and perioperative processes. Researchers have combined process mining with machine learning to analyze surgical workflows using electronic health record data, aiming to optimize activity sequences and reduce cycle times [21]. The MOVER EHR dataset, for instance, has enabled real-world analysis of surgical workflows, demonstrating how integrated approaches can identify inefficiencies invisible to traditional methods [21].

Interactive visual exploration tools have been developed to support collaborative analysis of surgical process data, allowing clinical teams—surgeons, anesthesiologists, nurse managers—to inspect variants, temporal patterns, and deviations in complex procedures [22]. These tools facilitate participatory sensemaking, helping reconcile clinical intuition with data-driven insights and building shared understanding of improvement priorities [22]. From a surgical training perspective, scholars have highlighted the importance of explicating step sequences as a key element for standardizing procedures and improving teaching quality, an area where process mining can contribute by revealing actual practice patterns [23].

Methodologically, pattern-based approaches for modeling process variability in healthcare contexts have been proposed, offering reusable solutions for representing alternative routes, conditions, and exceptions without sacrificing model clarity [24]. Recent work has demonstrated that integrating event attributes with transition features significantly enhances the descriptive power of process models in care pathway analysis [25]. Building on this foundation, optimal process mining techniques for traces with event and transition attributes have been developed and applied to cancer patient pathways, achieving superior results compared to widely used commercial tools [26]. Advanced conformance checking techniques, such as re-ordered fuzzy conformance checking, have been specifically designed to handle uncertain clinical records, enabling more robust analysis of real-world healthcare data [27]. Furthermore, studies assessing the feasibility of developing clinical pathways from order logs have shown both opportunities and limitations when records do not capture all relevant events [28].

D. Probabilistic and Stochastic Extensions for Surgical Decision Support

Complementing descriptive process mining, recent contributions have advanced toward predictive and prescriptive capabilities. Studies combining process mining with Bayesian networks have modeled patient flow in surgical wards, characterizing preoperative, anesthetic, surgical, and recovery phases while building patient-level predictive models for phase durations [29]. These probabilistic approaches enable estimation of expected completion times for new cases and assessment of how different combinations of clinical and organizational factors influence trajectory outcomes [29].

Stochastic workflow modeling represents further evolution, integrating process mining with simulation and control-flow structures that capture resource constraints, prioritization rules, and cancellation policies [30]. Applied to surgical settings, these models support both system-level simulation for capacity planning and individual-level decision support for daily scheduling [30]. Optimization frameworks incorporating predictive process monitoring have been developed for scheduling interventional radiology procedures, demonstrating how robust solutions can be generated under dynamic constraints [31]. Low-effort resource allocation optimization approaches have been proposed for dynamic environments, enabling healthcare organizations to respond rapidly to changing conditions [32]. Simulation studies for hip and knee replacement pathways have shown the feasibility of predicting stage durations and evaluating capacity scenarios before implementation [33].

E. Governance, Implementation, and the LMIC Gap

A recurrent finding across healthcare process mining literature is that technical capabilities alone are insufficient; governance structures and organizational adoption mechanisms are critical for translating analytical insights into sustained improvement [34]. Case studies on process mining governance in hospitals emphasize the need for clear roles and responsibilities for data capture, validation, and analysis, as well as formal spaces for reviewing results and deciding improvement actions [34]. Without these structures, process mining initiatives risk remaining one-off diagnostic exercises rather than becoming embedded in routine management practice [35].

The governance challenges documented in high-income settings—data quality, interoperability, skills gaps, and institutional resistance are amplified in LMIC public hospitals, where information systems are often siloed, digital maturity is low, and competing priorities limit investment in analytical capabilities [36]. Despite the proliferation of surgical process mining studies in recent years, literature still lacks integrated models that explicitly combine technical architecture, governance frameworks, and empirical validation tailored to public health systems in middle-income countries [37]. This gap is particularly acute in LMICs, where data fragmentation, skill gaps, and institutional resistance pose additional barriers [38]. Furthermore, existing frameworks seldom articulate how process mining outputs can be embedded into existing policy instruments—such as national surgical backlog reduction plans—or how they can support participatory decision-making cycles involving clinicians, managers, and information technology staff [39].

The model presented in Section 3 directly addresses these gaps by embedding governance within a scalable architecture validated in a Peruvian public hospital, thereby operationalizing the transferable framework called for in recent reviews [40].

III. Proposed Surgical Process Mining Model

A. *Model Overview*

The surgical process mining model presented here is designed as an integrated framework that combines technological, methodological, and organizational elements to transform fragmented clinical data into actionable insights for improving surgical efficiency. Its primary goal is to enable continuous improvement cycles by systematically capturing, analyzing, and interpreting perioperative data. The model's structure emerged from a synthesis of existing literature and was refined through consultations with clinical and operational experts, ensuring its relevance to resource-limited and digitally fragmented healthcare environments.

At the heart of the model lies a process mining engine that reconstructs surgical patient trajectories from event logs extracted from hospital information systems. This engine supports the discovery of actual process flows, the measurement of conformance against institutional protocols, and the identification of performance bottlenecks. Surrounding this core is a governance layer that ensures data quality, stakeholder engagement, and the translation of analytical findings into operational decisions. The model follows an iterative cycle—from data extraction to insight generation, intervention, and re-evaluation—emphasizing that process improvement is a continuous, learning-oriented activity rather than a one-time diagnostic exercise.

Figure 1 illustrates this iterative cycle, showing the five stages: (1) data extraction and event log construction, (2) process discovery and analysis, (3) interpretation and discussion in multidisciplinary committees, (4) implementation of improvement actions, and (5) re-evaluation and monitoring. The feedback arrows emphasize the continuous nature of the process.

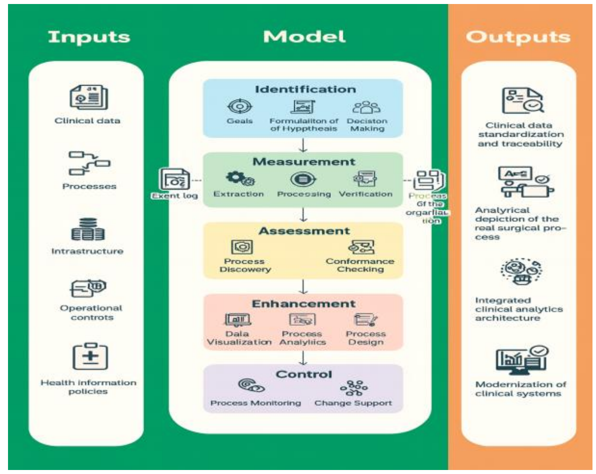

Fig. 1 Continuous improvement cycle of the surgical process mining model

B. *Inputs of the Model*

The model operates on five essential inputs, each addressing a critical aspect of the surgical care environment and its data ecosystem. These inputs were selected based on common challenges identified in literature and empirical observations from the case study, particularly the need to work with imperfect, fragmented data.

1) Clinical and administrative data: This includes all patient-level information generated during the surgical episode, such as demographics, diagnoses, procedure codes, anesthesia records, admission and discharge times, and cancellation or rescheduling events. In many settings, these data reside in multiple, disconnected systems (e.g., electronic health records, operating room scheduling software, laboratory systems). The model requires data to be extracted and harmonized, which often reveals inconsistencies and gaps—an important first step toward data quality improvement.

2) Process definitions: These are the formal descriptions of the intended surgical pathway, including clinical protocols, scheduling rules, and administrative workflows. They serve as a benchmark against which actual practice is compared. In the Peruvian context, such definitions are often outlined in national guidelines or institutional manuals, but they may not reflect day-to-day realities. The model uses these definitions to perform conformance checking, quantifying deviations and highlighting areas where practice diverges from policy.

3) Technological infrastructure: This refers to the hardware, software, and interoperability standards that enable data capture, integration, and analysis. In many public hospitals, infrastructure is limited and heterogeneous. The model is designed to be adaptable, working with basic data sources (e.g., spreadsheets or simple databases) in early stages and scaling to more sophisticated platforms as capacity grows. A layered architecture (detailed below) supports this flexibility.

4) Operational controls: These are the key performance indicators and management rules used to guide daily operations, such as waiting time targets, operating room utilization goals, cancellation rate thresholds, and scheduling policies. The model incorporates these controls to focus analysis on what matters most to managers and clinicians, and to generate alerts when performance deviates from acceptable ranges.

5) Health information policies: This input encompasses the legal, ethical, and organizational frameworks governing data use, privacy, and security. In Peru, these include national regulations and institutional guidelines. The model is designed to operate within these constraints, ensuring that all data handling complies with applicable norms and that governance structures are aligned with existing responsibilities.

C. Outputs of the Model

From the five inputs, the model generates five interrelated outputs that together create a comprehensive view of surgical process performance and provide a basis for action.

1) Standardized and traceable event logs: The process of building event logs forces the harmonization of identifiers, activity names, and timestamps across disparate systems. This output is a clean, structured dataset that can be used for ongoing monitoring and analysis. In the case study, constructing such a log revealed 39 distinct patient pathways, highlighting the degree of process variability.

2) Visual and quantitative process maps: Using process discovery algorithms, the model produces graphical representations of how surgeries unfold. These maps show the most common pathways, as well as infrequent or exceptional routes. They are complemented by metrics such as average duration, waiting times between activities, and frequencies of different paths. For managers and clinicians, these visuals make invisible patterns visible and facilitate discussions about where to intervene. A sample process map from the case study could be included to illustrate the complexity and variability.

3) Integrated analytics platform: The model promotes the development of a centralized data platform that consolidates information from multiple sources. This platform supports ad-hoc queries, dashboards, and deeper analyses, such as linking process performance to clinical outcomes (e.g., complications, length of stay). Over time, this becomes a valuable organizational asset for continuous improvement.

4) Operational dashboards and alerts: Key performance indicators derived from process mining are presented in user-friendly dashboards tailored to different audiences. For example, surgical chiefs might see weekly trends in cancellation rates by specialty, while nursing managers might monitor turnover times between cases. Alerts can be configured to notify staff when waiting times exceed thresholds or when conformance drops below acceptable levels. A mock-up of such a dashboard would help readers envision the practical application.

5) Governance and transparency framework: Finally, the model establishes clear roles, responsibilities, and routines for using process mining insights. This includes defining who has access to data, who is responsible for validating findings, and how decisions are made based on the analysis. In the Peruvian context, this framework can be linked to existing committees, such as those overseeing surgical backlog reduction, ensuring that process mining becomes embedded in ongoing management rather than remaining an external research project.

D. Technological Architecture

The technological backbone of the model is a four-layer architecture designed for scalability and adaptability to varying levels of digital maturity. Each layer has a distinct function, and together they form a pipeline from raw data to actionable intelligence. Figure 2 illustrates this architecture and the flow of data between layers.

1) Layer 1 – Source systems: This includes the various hospital information systems that generate data—electronic health records, operating room scheduling systems, admission/discharge logs, and any other relevant sources. These systems are often siloed and use different formats and identifiers. The architecture does not require them to be fully integrated; rather, it accepts data as they are and handles harmonization in the next layer.

2) Layer 2 – Data integration and preparation: In this layer, data are extracted, cleaned, and transformed into a unified event log. This involves mapping local terms to standardized activity names, reconciling patient identifiers, handling missing or inconsistent timestamps, and filtering out irrelevant events. The layer also performs initial quality checks and generates reports on data completeness and accuracy. For many hospitals, this layer is where the most significant work occurs, as it surfaces data quality issues that need to be addressed at the source.

3) Layer 3 – Process mining and analytics: This layer houses the algorithms for process discovery, conformance checking, and performance analysis. It takes the prepared event log and generates the outputs described earlier—process maps, conformance metrics, and performance indicators. The layer is designed to be flexible, allowing analysts to choose different algorithms depending on the research question or the characteristics of the data (e.g., using fuzzy mining for highly variable processes). It also supports drill-down capabilities, such as filtering by specialty or surgeon to compare performance across groups.

4) Layer 4 – Decision support and visualization: The top layer is where insights are delivered to end users. It includes interactive dashboards, automated reports, and alerting systems. This layer is designed with user experience in mind, presenting complex information in a clear and actionable format. It also supports what-if analysis and simulation, allowing managers to explore the potential impact of changes before implementing them.

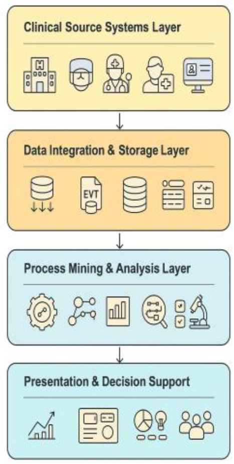

Fig. 2 Four-layer technological architecture of the surgical process mining model

E. *Governance and Implementation Considerations*

Successful implementation of the model requires more than technology; it demands a supportive organizational environment. Based on lessons from the case study and broader literature, we propose a governance structure that assigns clear roles and establishes regular routines for using process mining outputs.

1) Data steward: A designated individual (or team) responsible for overseeing data quality, managing the event log construction process, and ensuring that data handling complies with privacy and security policies. This role is typically housed in the IT or medical records department.

2) Process analyst: A specialist trained in process mining techniques who operates the software, conducts analyses, and produces dashboards and reports. In smaller hospitals, this role might be combined with the data steward, but in larger ones, dedicated analytical capacity is beneficial.

3) Surgical operations committee: A multidisciplinary group that meets regularly (e.g., monthly) to review process mining outputs, discuss findings, prioritize improvement initiatives, and assign responsibilities. This committee should include the data steward, clinical champion, process analyst, nursing management, and administrative representatives. Ideally, it is integrated with existing governance structures, such as the committee responsible for surgical backlog reduction, to avoid duplication and ensure alignment with organizational priorities.

The implementation should proceed in phases, recognizing that many hospitals have limited resources and capacity. An initial pilot might focus on a single surgical specialty or a high-volume procedure, using readily available data. As the team gains experience and trust, the scope can be expanded to include more services and more sophisticated analyses. Throughout, training and communication are essential to build understanding and buy-in among all stakeholders.

TABLE I. Phased implementation plan for the surgical process mining model

Phase	Objectives	Stakeholders
Phase 1: Pilot (Months 1–6)	Demonstrate feasibility, build trust, identify quick wins	Data steward, process analyst, clinical champion (surgeon or anesthesiologist), head of selected service
Phase 2: Expansion (Months 7–18)	Scale to all elective surgeries, establish governance routines	Expanded committee (includes nursing managers, administrative staff), IT support
Phase 3: Integration (Months 19–36)	Embed into daily management, enable predictive capabilities	Full surgical operations committee, hospital management, quality/safety department

The framework's design—with its emphasis on governance, scalability, and alignment with existing policies—directly addresses the barriers identified in the case study, where 73% of experts flagged data quality and interoperability as major challenges. By providing a structured yet flexible framework, it offers a pathway for hospitals in Peru and similar settings to move from fragmented data to evidence-based improvement.

IV. Process Mining Methodology

A. *Study Setting and Data Sources*

The study was conducted in a tertiary public hospital in Peru, characterized by high surgical demand and structural constraints. Data was extracted from the hospital's information systems by the IT area, in compliance with clinical data confidentiality and protection policies. The extraction ensured the minimum structure required for process mining: a unique case identifier (surgical episode), activities corresponding to the pre-, intra-, and postoperative flow, and timestamps for each activity.

Data were extracted from three source systems: the admission–discharge–transfer system, the surgical scheduling module, and the anesthesia and recovery information system. A reconciliation procedure based on the patient's unique medical record number and the surgical episode date was applied to harmonize identifiers across systems. Of the initial 1,685 episodes, 451 were excluded due to missing critical timestamps, inconsistent temporal sequences, or duplicate records. The remaining 3.2% of missing timestamps in non-critical activities were imputed using median durations.

The final event log comprised 12 standardized activities (Table III).

B. Event Log Construction and Data Processing

A total of 1,685 surgical episodes were initially extracted from the hospital's systems. After applying rigorous data cleaning and quality assurance procedures—excluding records with missing critical timestamps, inconsistent activity sequences, or registration errors—the final event log comprised 1,234 cases and 9,872 events.

The dataset covered 8 operating rooms and 2 types of surgical encounters (scheduled and emergency). The most frequent process variant accounted for 74.6% of cases, with a throughput time of 20 hours. Table 1 summarizes the event log characteristics.

TABLE II. Summary of the Surgical Process Event Log

Attribute	Value
Number of cases (surgical episodes)	1,234
Number of events	9,872
Number of distinct activities	12
Number of operating rooms	8
Case types	Scheduled (82%), Emergency (18%)
Time period	January 2023 – March 2024
Most frequent variant	74.6% of cases
Number of process variants (total)	39
Average events per case	8.0
Median throughput time (all cases)	11 hours
Data completeness (timestamps present)	96.8%

TABLE III. Mapping Source Fields to Standardized Event Log Activities

Source system	Standardized activity	Lifecycle phase
Admission timestamp (Admission–Discharge–Transfer system)	Patient admission	Preoperative
Preoperative evaluation completion (Nursing records	Preoperative preparation	Preoperative
Operating room entry time (Surgical scheduling module)	Transfer to Operation Room	Intraoperative
Anesthesia start (Anesthesia information system)	Anesthesia induction	Intraoperative
Incision time (Surgical scheduling module)	Surgery start	Intraoperative
Closure time (Surgical scheduling module)	Surgery end	Intraoperative
Recovery admission time (Anesthesia information system)	Transfer to recovery	Postoperative
Recovery discharge time (Anesthesia information system)	Discharge from recovery	Postoperative

C. *Process Discovery with Celonis*

The Celonis platform was used for process mining analysis. After loading the data, initial metrics were generated: an average of 15 cases per day, 135 events per day, and an average process duration of 11 hours (excluding outliers). Process discovery was performed using the Fuzzy Miner algorithm. Due to the initial complexity ("spaghetti effect" at 100% of connections), the model was filtered to 99.1% of activities, covering variants with frequency >1% and excluding infrequent behavior.

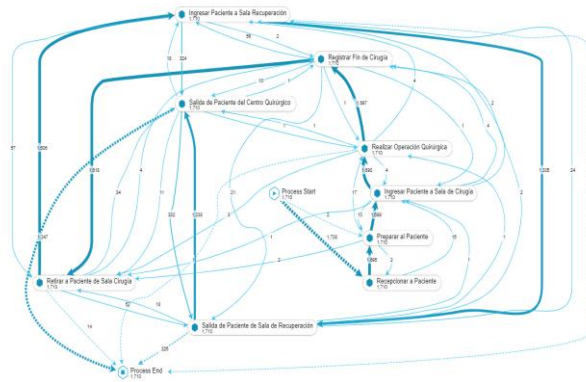

Fig. 3 Model discovered 100% of connections by Celonis

D. Bottleneck Identification

Performance analysis revealed a critical bottleneck between the activities "Patient admission" and "Preoperative preparation", with a median waiting time of 15 hours (IQR: 11–19 hours). This waiting time accounted for 62.5% of the total planned preoperative stay (24 hours). Secondary bottlenecks were observed between surgery end and transfer to recovery (median 45 minutes, IQR: 30–75 minutes) and between transfer to recovery and discharge (median 120 minutes, IQR: 90–180 minutes).

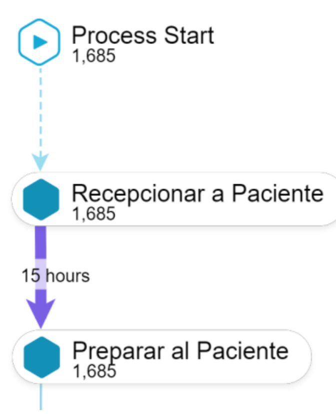

Fig. 4 Bottleneck Process Discovering

E. Conformance Checking

Conformance checking was performed using alignments-based conformance checking implemented in PM4Py (v. 2.7.11). The reference model — a BPMN diagram co-designed with the Head of Surgery from the institutional protocol— was configured with standard cost parameters (log move = 1, model move = 1) and no trace filtering. Fitness was

0.75, precision 0.68, and generalisation 0.82. Twenty-one distinct violations were detected, concentrated in two patterns: omission of "Preoperative preparation" (8.2% of non-conforming traces) and out-of-sequence transfers (4.3%). A sensitivity analysis excluding these traces raised fitness to 0.83, confirming that non-conformances were concentrated in a bounded subset of variants.

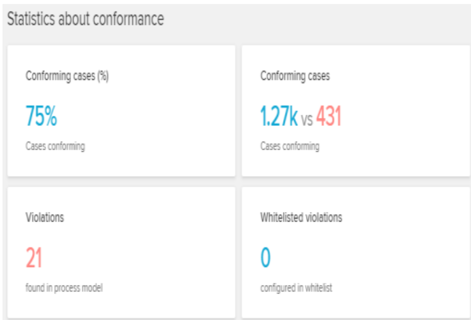

Fig. 5 Conformance Checking

V. Expert Validation Methodology

A. Data Collection

A questionnaire was employed for data collection. An online survey in Spanish was designed using Google Forms (https://forms.gle/hRj5SHSCctuYqgfp7), based on the proposed model. The survey was administered between July and November 2025 to 15 medical specialists involved in surgical procedures, including surgeons, anesthesiologists, resident physicians, and surgical nursing staff. Its purpose was to capture the perceptions of these professionals regarding the model's potential to enhance operational efficiency within the Peruvian healthcare system.

The survey is structured into three sections. Section 1 collects general demographic and professional information (six items). Section 2 explores participants' perceptions of critical success factors for the framework (eight items). Section 3 examines the overall assessment of the framework and the intention to adopt it (three items: perceived usefulness [UTIL], willingness to use [DISP], implementation feasibility [FACT]). Items in Sections 2 and 3 were measured using a five-point Likert scale (1 = Very low, 2 = Low, 3 = Intermediate, 4 = High, 5 = Very high).

After preparing the survey, a pilot test was conducted to validate the questions. The pilot test was carried out by a surgical anesthesiologist with more than 10 years of experience, who verified whether the items were adequately related to the hypotheses. The wording of the questions was corrected to guarantee the use of appropriate language. The survey was completed in-person by surgical specialists from several health centers in Lima, Peru. In total, 15 responses were obtained.

B. Results analysis

1) Reliability: reliability and internal consistency using Cronbach's alpha.
2) Descriptive statistics: Means, standard deviations, and distributions for all items.
3)Simple Correspondence Analysis (SCA): To explore associations between professional experience levels and perceptions of UTIL, DISP, and FACT.
4) Hypothesis testing: Paired t-tests to compare mean ratings of UTIL, DISP, and FACT, and independent t-tests to explore differences by gender, institution type, and education level.

VI. Process Mining Results

A. Event Log Characteristics

The final event log comprised 1,234 cases and 9,872 events, with an average of 8 events per case. The most frequent activities were patient admission and discharge from recovery (present in 100% of cases). Missing timestamps were identified in 3.2% of activities and were imputed using median durations for the same activity and specialty.

B. Process Variants

The Fuzzy Miner algorithm, complemented by variant analysis, discovered 39 distinct process variants. The most frequent variant, followed by 74.6% of cases, corresponded to the standard sequence: admission → preoperative preparation → transfer to OR → anesthesia induction → surgery start → surgery end → transfer to recovery → discharge from recovery. The remaining 25.4% of cases followed alternative sequences. Table 4 lists the five most common variants.

TABLE IV. Five Most Frequent Process Variants

Rank	Variant Description	Frequency (%)	Median Throughput Time
1	Standard sequence (as above)	74.6%	20 hours
2	Omission of preoperative preparation	8.2%	16 hours
3	Repeated preoperative preparation	5.1%	28 hours
4	Transfer to recovery before surgery end (data error or real event)	4.3%	N/A
5	Surgery cancelled after admission	3.5%	5 hours (until cancellation)

C. Bottleneck identification

Performance analysis revealed a critical bottleneck between patient admission and preoperative preparation, with a median waiting time of 15 hours (IQR: 11–19 hours). This waiting time accounted for 62.5% of the total planned preoperative stay (24 hours). Secondary bottlenecks were observed between surgery end and transfer to recovery (median 45 minutes, IQR: 30–75 minutes) and between transfer to recovery and discharge (median 120 minutes, IQR:

90–180 minutes). Figure 4 presents a boxplot of waiting times for these key transitions

D. Conformance checking

Alignments-based conformance checking yielded a fitness score of 0.75, indicating that 75% of the observed behavior could be replayed on the institutional protocol model without violations. Precision was 0.68, suggesting that the model allows for some behavior not observed in the log. Generalization was 0.82, indicating good ability to generalize to new cases. A total of 21 distinct violations were identified, most related to the omission of preoperative preparation and out-of-sequence transfers.

VII. Expert Validation Results

A. Data reliability

Cronbach's alpha was used to estimate data reliability. For the eleven items corresponding to the critical success factors and implementation dimensions (Sections 2 and 3), Cronbach's alpha was calculated using R software based on the 15 valid responses. The analysis yielded a Cronbach's alpha of 0.89, confirming excellent internal consistency. This value indicates that the items reliably measure the perceived influence of critical factors on surgical process optimization, as well as the associated dimensions of usefulness, willingness to use, and implementation feasibility. No substantial increase in alpha was observed by deleting any single item, supporting the retention of all eleven items in the scale.

B. Descriptive analysis of the study population

A total of 15 valid responses were analyzed, corresponding to healthcare professionals with experience in surgical processes. Regarding the demographic profile, 73.3% of participants were men (n=11) and 26.7% women (n=4). The majority of respondents (73.3%, n=11) worked in public hospitals, while 20% (n=3) belonged to private clinics and 6.7% (n=1) to educational institutions. Concerning the position held, 80% (n=12) worked as medical professionals, followed by hospital directors or managers (13.3%, n=2), heads of surgical services or units (6.7%, n=1), and other positions (6.7%, n=1). Regarding educational level, 66.7% (n=10) held a master's degree, 20% (n=3) a bachelor's degree, 6.7% (n=1) a doctorate, and 6.7% (n=1) indicated another degree. Experience in the field of surgical processes showed a heterogeneous distribution: 33.3% (n=5) reported between 1 and 3 years of experience, 26.7% (n=4) less than 1 year, 20% (n=3) more than 10 years, 13.3% (n=2) between 4 and 6 years, and 6.7% (n=1) between 7 and 10 years.

C. SCA

The Simple Correspondence Analysis performed on the three implementation dimensions explained 89.7% of the total variance (Dimension 1: 58.4%; Dimension 2: 31.3%), revealing distinct perceptual patterns across experience levels. Novice professionals with less than one year of experience showed strong associations with usefulness (UTIL) and willingness to use (DISP), reflecting their optimism and readiness to adopt the model based on recent academic exposure to data-driven methodologies. Mid-career professionals (4–10 years of experience) clustered together and demonstrated stronger associations with implementation feasibility, indicating that those engaged in day-to-day operational management are more attuned to the practical constraints, resource limitations, and organizational barriers that affect real-world adoption. Senior professionals with more than ten years of experience showed balanced associations but were positioned closer to willingness to use, suggesting that extensive organizational experience leads to recognition that successful implementation depends not only on technical solutions but on the readiness of clinical staff to embrace new tools. These findings demonstrate that perceptions of implementation dimensions evolve along the professional trajectory, from novice optimism about value and adoption, through mid-career pragmatism about feasibility constraints, to senior recognition of the organizational and cultural readiness required for sustainable implementation.

The Student's t-test analysis of the three implementation dimensions revealed no statistically significant differences between groups based on gender, institution type, or educational level, although medium effect sizes suggested potentially meaningful variations that did not reach significance due to the small sample size. Females consistently rated all dimensions higher than males, particularly usefulness ($d = 0.62$) and feasibility ($d = 0.52$), while public hospital respondents showed moderately higher willingness to use ($d = 0.59$) and feasibility perceptions ($d = 0.63$) compared to private clinic respondents. Most notably, paired comparisons revealed a significant gap between willingness to use (DISP, mean = 4.63) and implementation feasibility (FACT, mean = 4.00), with a mean difference of 0.63 ($p = 0.001$, Cohen's $d = 1.01$), indicating a large practical effect. Similarly, perceived usefulness (UTIL, mean = 4.50) significantly exceeded implementation feasibility by 0.50 points ($p = 0.010$, $d = 0.77$). These findings highlight a critical challenge: while professionals express strong willingness to adopt the model and recognize its utility, they perceive significantly lower feasibility for its actual implementation in their institutions, suggesting that organizational and resource-related barriers may impede real-world adoption despite positive attitudes toward the model's value.

VIII. Case Discussion And Future Research

The process mining analysis uncovered systemic inefficiencies consistent with regional evidence on preventable surgical cancellations [2], [4]. The 15-hour bottleneck between admission and preoperative preparation (62.5% of planned stay) reflects fragmented coordination among admission, nursing, and anaesthesia services. Secondary bottlenecks between surgery end and transfer to recovery (median 45 minutes) and between transfer to recovery and discharge (median 120 minutes) confirm that delays accumulate across multiple perioperative transitions. The 39 distinct process variants—25.4% of cases deviating from protocol—reveal extreme pathway fragmentation. Specific variants such as omission of preoperative preparation (8.2%) and repeated preoperative preparation (5.1%, throughput time inflated to 28 hours) directly impact operational efficiency and patient safety. The conformance rate of 75% (fitness = 0.75) quantifies the protocol gap. A sensitivity analysis excluding the two dominant violation patterns (omission and out-of-sequence transfers at 4.3%) raised fitness to 0.83, confirming that non-conformances are concentrated and addressable through targeted interventions.

Expert validation confirmed the model's relevance, with integration of information between areas (4.81/5) and active participation of medical staff (4.75/5) as top success factors, echoing governance literature [34], [35]. However, a significant gap ($p = 0.001$, $d = 1.01$) between willingness to use (4.63) and perceived feasibility (4.00) reveals a critical tension: professionals recognize the model's value—usefulness also scored 4.50—yet harbor substantial deployment concerns, consistent with documented LMIC challenges around data fragmentation and interoperability [36], [38]. Notably, 73% of experts flagged data quality and interoperability as major barriers, reinforcing the need to address infrastructural constraints alongside technical development.

The Simple Correspondence Analysis distinguished perceptual patterns across career stages: novice optimism about usefulness, mid-career pragmatism regarding feasibility, and senior recognition that sustainable implementation requires both technical and cultural readiness. These evolving perceptions underscore the need for stakeholder-tailored implementation strategies—leveraging novice enthusiasm, mid-career realism, and senior organizational experience.

Several limitations must be acknowledged. The single-hospital design limits generalizability. Event log construction relied on existing systems, and the 451 excluded episodes (26.8% of the initial sample) could introduce selection bias. The expert sample, though reliable ($\alpha = 0.89$), was small ($n = 15$), limiting statistical power; medium effect sizes for gender ($d = 0.62$) and institution type ($d = 0.63$) warrant larger, more diverse samples.

Future research should pursue four directions. First, multi-site validation across hospitals with varying digital maturity is essential to test the model's transferability. Second, data quality must be strengthened through standardized recording protocols and automated timestamp capture. Third, the phased implementation plan (Section III-E) should be operationalized through action research to address organizational barriers. Finally, the architecture should evolve toward proactive decision support, embedding real-time dashboards in Layer 4 for continuous monitoring and predictive models in Layer 3 for forecasting surgery duration and cancellation risk, in line with the probabilistic and stochastic approaches discussed earlier [29], [30] and Peru's Surgical Backlog Reduction Plan [5].

IX. Conclusions

This research demonstrates that the primary barrier to improving surgical efficiency in resource-constrained public hospitals is not merely a lack of data, but a lack of governance-aware frameworks to interpret and act upon it. By empirically validating a sociotechnical framework that couples technical rigor with an explicit focus on organizational feasibility, we provide a tangible pathway for LMIC health systems to move beyond reactive backlog management toward proactive, data-driven process optimization.

The proof-of-concept in a Peruvian tertiary hospital revealed previously invisible inefficiencies—a 15-hour preoperative bottleneck, 39 process variants, and a conformance rate of 75%—demonstrating the framework’s diagnostic power. Expert validation confirmed the relevance of the framework but also uncovered a critical gap between its high perceived usefulness and lower implementation feasibility. This gap serves as a call to action: future efforts must invest as much in building organizational capacity, trust, and governance structures as in developing analytical tools.

The framework’s phased implementation plan, governance structure, and alignment with national backlog reduction policies offer a concrete blueprint for hospitals in Peru and similar settings. By addressing the intertwined technical and organizational challenges, this study contributes not just a method, but a mindset for sustainable surgical systems improvement in low- and middle-income countries.

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