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RESEARCH ARTICLE

MedProSim: A Process Mining-Based Simulation Tool for Identifying the Causes of Waiting Times in Outpatient Departments

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ABSTRACT This study aims to reduce outpatient waiting times by introducing a two-phased framework that diagnoses existing delays in an ''as-is'' phase and proposes operational improvement through targeted simulation in a ''to-be'' phase. The framework is designed to identify delay sources within patient interactions and enable data-driven adjustments to optimize patient flow. In the diagnosis phase, waiting times are categorized based on distinct patient interactions to provide a detailed analysis of delay sources. Key indicators, specifically patient arrival density, consultation interval variability, and prolonged consultation time ratio, are identified, and a dotted chart analysis is utilized to visualize delay patterns. Subsequently, scenarios targeting each indicator are developed and tested with MedProSim, a custom-built simulation tool that allows administrators to simulate potential changes prior to actual implementation. A case study conducted in the rheumatology and pulmonology departments of a Korean tertiary hospital highlights department-specific delay sources and demonstrates the effectiveness of targeted interventions. In pulmonology, patterns in patient arrival, consultation intervals, and extended consultation times are identified as significant contributors to delays. Simulated interventions, such as scheduling adjustments and grouping strategies, effectively reduced waiting times, validating the potential of the framework to improve patient flow. This study provides a structured framework with distinctive definitions of waiting times and multiple performance indicators, enabling administrators to make informed, data-driven adjustments to hospital operations.

INDEX TERMS Appointment scheduling, outpatient flow optimization, process mining, simulation, waiting time.

I. INTRODUCTION

The rapid expansion of healthcare data has presented significant opportunities to enhance operational efficiency in hospitals. Among various data sources, event logs from Hospital Information Systems (HIS) provide critical insights into patient flows, which are essential for analyzing and optimizing operations. Waiting times are one of the important performance indicators, as they directly influence both operational efficiency and patient satisfaction. Long waiting times and consequent prolonged total visit time can undermine hospital performance, lower patient satisfaction, potentially contributing to congestion in waiting areas or parking facilities.

While reducing waiting times is essential, many studies focus on Door-to-Doctor time (DTD) [1], [2], [3], [4] which measures the total time from a patient's arrival at the hospital to the start of their consultation and treatment.

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DTD is effective for identifying broader issues such as waiting area congestion or parking inefficiencies. However, it fails to capture delays caused by ineffective appointment systems. Additionally, existing research often overlooks the potential of process mining techniques, concentrating on discrete-event simulation (DES) to model patient flows. Although promising, data-driven process simulation (DDPS) within the process mining context remains underutilized [39] and there is still a gap between theoretical research and practical application.

To address these gaps, this study proposes a novel approach that combines process mining and simulation techniques to reduce outpatient waiting times. Instead of using DTD only, we adopt a more granular definition of waiting times and focus on specific delays related to hospital inefficiencies. The goal is to improve the current appointment system by analyzing delays due to the inefficiency present on the hospital side while excluding patient-related factors such as late arrivals. To support this approach, the study develops a web-based tool to diagnose inefficiencies and explore operational improvements.

RQ 1: How should waiting times be defined in outpatient clinics and what are the key factors contributing to these waiting times?

RQ 2: How can we accurately diagnose current delay patterns and identify the underlying causes of these delays?

RQ 3: What are the most effective what-if scenarios for reducing waiting times, and how can these scenarios be validated through simulation?

RQ1 is addressed by an event-log-based operationalization of waiting-time KPIs. Specifically, we define clinically meaningful reference timestamps that are consistently recorded in the outpatient event log (e.g., clinical check-in/clinical readiness, consultation start, and scheduled appointment time) and formalize appointment-related waiting and schedule deviation as time differences between these events. This process-aware KPI design constitutes the measurement foundation of the process mining lifecycle, enabling subsequent discovery-based diagnosis (RQ2) and simulation-based improvement evaluation (RQ3) on a common, reproducible data representation. For RQ2, we employ process discovery-oriented analysis—specifically dotted chart analysis—to visualize the observed patient flow directly from the event log without imposing an a priori process model, thereby revealing hidden bottlenecks and behavioral patterns (e.g., batching effects) that complement aggregate descriptive statistics. For RQ3, we conduct process enhancement by calibrating a data-driven discrete-event simulation model using parameters, process variants, and historical distributions extracted from the discovered event-log patterns, which enables realistic what-if evaluation of scheduling policies for operational improvement.

II. RELATED WORKS

Recent works on healthcare simulation have focused on analyzing historical patient flow and proposing process improvements through various scenarios, targeting specific processes and employing diverse simulation methods. Depending on the process type, studies have concentrated on specific areas in a hospital such as emergency department (ED) [5], [6], intensive care unit (ICU) [7], operation rooms [8], blood collection counters [9], problematic departments [10], [11], outpatient clinics [12], [13], or entire hospitals [14], [15]. Regarding simulation methods, discrete-event simulation (DES) is the most frequently used approach [8], [9], [16], [17], [18], [19] whereas other studies have utilized agent-based simulation (ABS) [20], Monte Carlo simulation [21], or hybrid models combining DES and ABS [22]. While existing simulation studies do not incorporate process mining, this paper presents a DES-based process simulation of outpatient departments that leverages insights derived from process mining of real hospital data.

In existing studies of outpatient departments, most of them are aimed at reducing waiting times, between patient arrival and subsequent services, such as physician consultation, surgical procedures, or diagnostic examinations such as MRI [1], [2], [3], [4], [8], [16], [21], [24]. For example, in [8], patient waiting time is defined as the time patients wait for surgery after all preparations are completed, while in [24], classify waiting time into two categories: waiting for MRI and waiting for a radiologist. Only a few studies utilize multiple definitions of waiting time. For instance, ben Sghaier and Mraihi [14] differentiate between waiting for registration and waiting for appointment, while De Santis et al. [5] focus on both door-to-doctor time (DOT) and doctor-to-discharge time (DIT). Among the reviewed papers, only Robielos et al. [23] introduce the concept of 'micro waiting time,' which is categorized into three types of waiting times: waiting time 1 (WT 1: time from patient arrival to tracer number issuance), WT 2 (time waiting for the tracer number to appear on the screen for vital sign check, and WT 3 (time waiting for consultation after registration). As such, several existing studies primarily compare actual delays with simulated delays using typical metrics, often overlooking a more precise diagnosis of the current situation. Consequently, they typically use simple metrics such as average waiting time, max queue length, or total length of stay, without considering more comprehensive metrics that could provide a deeper understanding of the current situation in the hospital [18], [25], [26].

Although existing studies have focused on reducing actual waiting times, limited attention has been given to exploring alternative appointment strategies. Instead, several existing studies apply a broader range of scenarios, including resource allocation [30], [31], resource addition [32], staff scheduling [10], [23], and the combination of resource, environment, and process-related changes [33]. Some studies even examine the introduction of new systems [34]. Among those addressing appointment policies, Venkatesan et al. [18] evaluate a scenario that involves the introduction of fixed-interval appointment scheduling and review different appointment rules. Missaoui and Boujelben [27] employ a simulation-based approach to implement outpatient appointment system, applying three scheduling rules combined with four appointment rules. In Pan et al. [28], two different appointment policies have been tested and one of them for dilation-free examination is expected to have a positive impact on reducing patient waiting times. In Luo et al. [29], again, two policies, i.e., one hour interval and 0.5 hour interval, are tested for impacts on waiting times, and focused only on patient's punctuality. In this study, we examine three different appointment policies for two outpatient departments, with more granular definition of delays.

In addition, while existing studies on healthcare process simulation employ DES, process mining (PM) techniques are relatively less explored. To minimize waiting times, several studies exploit optimization tools [5], [38] or machine learning techniques [7], [38], but PM techniques are rarely applied. From the PM perspective, data-driven process simulation (DDPS) is still in its early stages [39]. Among the studies on PM-supported simulation, the focus is often on developing automated methods for discovering process models [40] or leveraging PM techniques to simulate a specific department to test different strategies [41], [42]. As studies aimed at reducing waiting times using PM techniques, several studies are relevant. Zhou et al. [35] suggest the number of staff members to improve outpatient processes using process discovery algorithms. Similarly, Antunes et al. [36] propose a three-staged approach to reduce patient waiting times, encompassing process identification, process optimization, and process simulation. In this study, we utilize the components suggested in Martin et al. [37] in the context of Business Process Simulation (BPS), such as activity duration and queue discipline.

Lastly, this paper aims to provide a tool that is specifically designed for performance analysis and process simulation in healthcare. While numerous studies suggest, apply, evaluate multiple scenarios using existing tools such as Arena, AnyLogic, FlexSim, or ProModel, the development of novel tools is hardly observed. Among the limited studies that propose tools for decision-making in hospital processes, Ordu et al. [15] present a decision support system based on discrete-event simulation. Additionally, Choi et al. [43] suggest a simulation-based operation management system to more efficiently manage outpatient departments in university hospitals. The lack of intuitive tools could present a significant barrier to the practical implementation of suggested process improvements. Therefore, there is a clear research need for developing tools that are readily accessible to medical professionals, facilitating the smooth implementation of healthcare process simulation models.

III. AS-IS ANALYSIS

This study adopts a two-phased framework that integrates event-log-based measurement, discovery-oriented diagnosis, and enhancement-oriented what-if evaluation. We emphasize that our use of process mining focuses on event-log-based KPI operationalization, discovery-oriented diagnosis, and enhancement-oriented evaluation; formal conformance checking against a prescriptive reference model is outside the scope of this study.

The as-is phase establishes the measurement and diagnostic foundation by (i) preparing outpatient event logs, (ii) operationalizing waiting-time KPIs directly from event-log timestamps (RQ1), where the clinic-attributable waiting is defined as CCT when the scheduled appointment time occurs before clinical check-in, and as ACT when it occurs after clinical check-in, and (iii) diagnosing dominant delay mechanisms using process discovery-oriented analysis, including dotted chart visualization and descriptive statistics (RQ2). The to-be phase corresponds to process enhancement, where scheduling interventions are formulated and evaluated via data-driven process simulation calibrated from the observed event-log patterns (RQ3). Figure 1 summarizes this alignment between phases and process mining components.

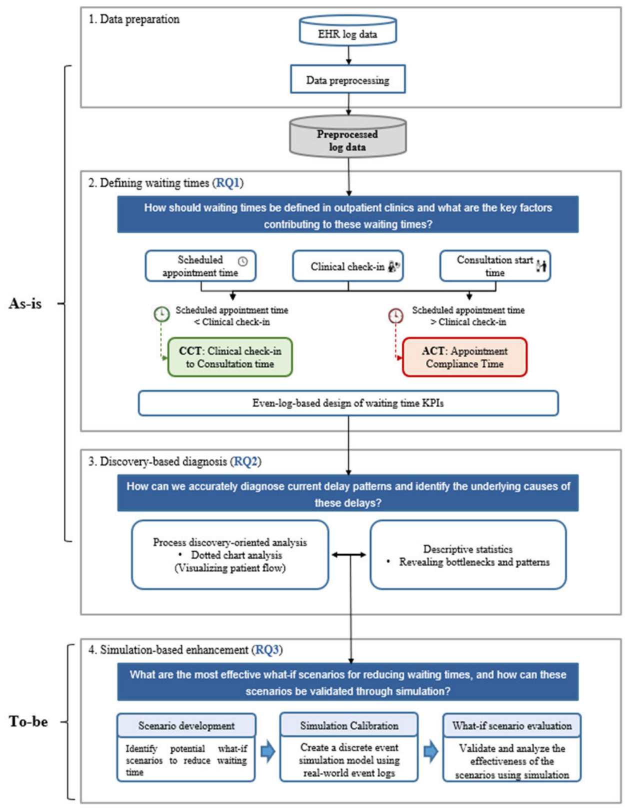


FIGURE 1. The proposed framework.

A. DATA PREPARATION (EVENT LOG PREPARATION)

Event logs are extracted from Electronic Health Records (EHR) and preprocessed to ensure data consistency and relevance for analysis. This step involves cleaning and structuring data to capture the accurate sequence and timing.

B. DEFINE WAITING TIMES (EVENT-LOG-BASED KPI OPERATIONALIZATION; RQ1)

In outpatient settings, waiting time is often a primary determinant of patient satisfaction. However, a single metric

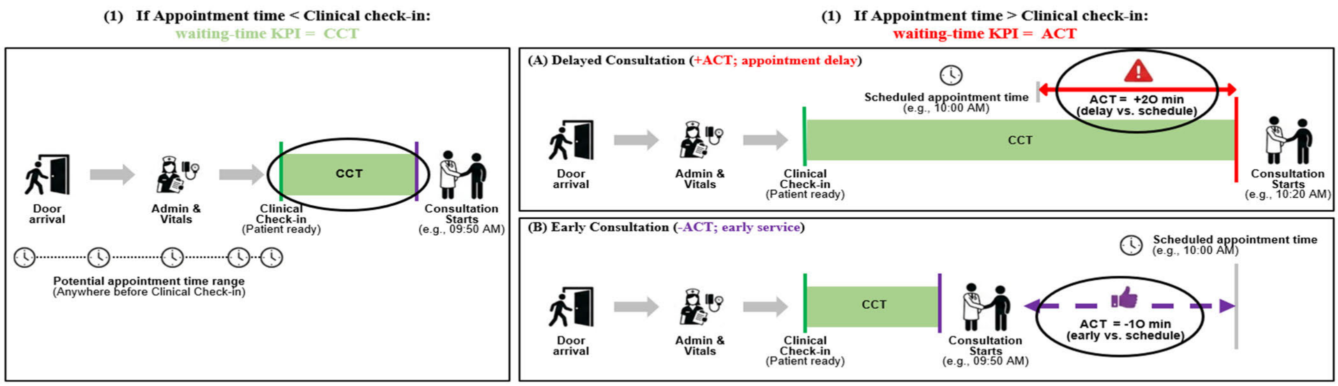


FIGURE 2. Two waiting times in patient flow.

like total waiting time (Door-to-Doctor) can be misleading because it aggregates delays caused by hospital inefficiencies with those caused by patient behaviors (e.g., arriving early). To address this, we define two appointment-related time-based KPIs: Clinical Check-in to Consultation Time (CCT) and Appointment Compliance Time (ACT). CCT captures clinic-attributable waiting after clinical readiness, whereas ACT captures deviation from the scheduled appointment time (delay or advance). Which measure is most relevant depends on whether the scheduled appointment time occurs before or after Clinical Check-in, as illustrated in Fig. 2.

CCT measures the duration from the moment a patient is clinically ready to see the doctor until the consultation actually begins. Clinical Check-in does not refer to the administrative arrival at the front desk. Instead, it is the specific timestamp recorded by a nurse after all preliminary assessments-such as vital sign measurements and history taking-are completed. This timestamp marks the point where the patient is fully prepared for the physician. Any wait time after Clinical Check-in is a "pure" wait attributable to the physician's unavailability or workflow bottlenecks, rather than administrative processing.

ACT measures the discrepancy between the scheduled appointment time and the actual start of the consultation (ACT = consultation start − scheduled appointment time). A positive value indicates that the consultation began after the scheduled time (appointment delay), whereas a negative value indicates that the consultation began before the scheduled time (early service). Importantly, ACT is a schedule-deviation metric rather than a pure waiting-time measure; it should be interpreted as appointment-related waiting only when the scheduled appointment time occurs after Clinical Check-in. When the scheduled appointment time occurs before Clinical Check-in, the patient is not yet clinically ready and the clinic-attributable waiting is better represented by CCT; when the scheduled appointment time occurs after Clinical Check-in, the patient is already ready and ACT directly represents appointment-related delay/advance relative to the schedule. By distinguishing these cases, improvement efforts can focus on reducing (i) excessive CCT (physician-queue waiting) and (ii) large positive ACT (schedule violation), without conflating delays with pre-consultation preparation.

This figure clarifies two appointment-related waiting-time KPIs using key timestamps along the patient journey: door arrival, administrative check-in and vitals, clinical check-in (the time at which the patient is recorded as clinically ready for the physician), and consultation start. (1) If the scheduled appointment time occurs before clinical check-in, this study quantifies clinic-attributable waiting using CCT, which represents the pure physician-queue waiting time after the patient is clinically ready. Because the patient is not yet ready before clinical check-in, the appointment time can fall anywhere prior to this point and does not directly represent physician waiting. (2) If the scheduled appointment time occurs after clinical check-in, this study uses ACT as the waiting-time KPI (appointment compliance), defined as the deviation between the scheduled appointment time and the actual consultation start, while CCT is shown to indicate the physician-queue time after readiness. Panel (A) illustrates a delayed consultation with positive ACT (e.g., +20 min), indicating the consultation begins after the scheduled time. Panel (B) illustrates an early consultation with negative ACT (e.g., −10 min), indicating the consultation begins before the scheduled time (early service).

C. PERFORMANCE ANALYSIS (PROCESS DISCOVERY-ORIENTED DIAGNOSIS; RQ2)

Performance analysis includes descriptive statistics and dotted chart analysis to investigate causes of delays. Descriptive statistics provide an overview of the current situation, while dotted chart analysis, combined with the waiting time indices, offers a visual and quantitative examination of temporal patterns. This analysis helps identify the specific reasons for delays, such as patient overcrowding, physician schedule delays, or extraordinarily lengthy consultation times.

1) DESCRIPTIVE STATISTICS

For descriptive statistics, we use two steps to analyze delays. First, we compare days with delays to those without delays for each physician by calculating the average waiting time over a predefined period. Days where the daily average waiting time exceeds the total average are classified as "days with delays", and the rest "days without delays". Then, we calculate three indicators: Patient Arrival Density (PAD), Consultation Interval Variability (CIV), and Prolonged Consultation Time Ratio (PCTR), and perform t-tests to examine statistical differences between delayed and non-delayed days. This comparison helps determine whether each indicator significantly impacts waiting times, identifying primary delay factors. PAD measures patient arrival concentration and indicates overcrowding; CIV quantifies the variability in time intervals between the end time of a consultation and the start time of the next consultation, revealing the effects of scheduling gaps or unexpected disruptions. Meanwhile, PCTR quantifies prolonged consultation times, often linked to complex cases or unexpected issues occur during consultation. These indicators collectively provide insights regarding diverse delay sources, from patient flow and physician availability to consultation complexity.

a: PATIENT ARRIVAL DENSITY (PAD)

The PAD quantifies the concentration of patient arrivals in daily time slots to assess arrival variability, which impacts waiting times. It is calculated as follows:

1) Divide the day into time slots (e.g., 9:00-10:00).
2) Calculate the patient ratio per time slot P_i :

$$P_i = \frac{Number\ of\ patients\ arriving\ in\ time\ slot\ t_i}{Total\ number\ of\ patients}$$

3) Compute the average ratio $\bar{P}$:

$$\bar{P} = \frac{1}{k}\sum_{i=1}^{k} P_i,\ where\ k\ is\ the\ number\ of\ time\ slots.$$

4) Calculate the standard deviation:

$$\text{PAD} = \sqrt{\frac{1}{k}\sum\nolimits_{i=1}^{k}\left(P_i - \bar{P}\right)^2} \tag{1}$$

b: CONSULTATION INTERVAL VARIABILITY (CIV)

The CIV measures the time interval between the end time of a consultation and the start time of the next consultation to assess the impact of non-consultation periods on waiting times.

1) Calculate Inter-consultation time (IcT): Measure the interval between the end of the consultation for the ith patient and the start of the consultation for the (i+1)th patient, where CET refers to the exact time the consultation ends for each patient, and CST is the start time for the next consultation:

$$IcT_i = CST_{(i+1)} - CET_i$$

2) Measure average interval AI:

$$\text{AI} = \frac{\sum_{i=1}^{N-1} IcT_i}{N-1}$$

3) Calculate CIV:

$$\text{CIV} = \sqrt{\frac{1}{N-1}\sum\nolimits_{i=1}^{N-1}\left(IcT_i - \text{AI}\right)^2} \tag{2}$$

c: PROLONGED CONSULTATION TIME RATIO (PCTR)

The PCTR quantifies the average time of consultations that exceed the average duration to assess the impact of prolonged consultation sessions on waiting times.

1) Calculate average consultation time ACT: CT_i is the consultation time for the ith patient and N is the total number of consultations.

$$\text{ACT} = \frac{1}{N}\sum\nolimits_{i=1}^{N} CT_i,$$

2) Calculate PCTR:

$$\text{PCTR} = \frac{\sum_{i=1}^{N}\left(CT_i - ACT\right)}{Number\ of\ prolonged\ consultations},$$
$$where\ CT_i > ACT \tag{3}$$

2) DOTTED CHART ANALYSIS

Dotted chart analysis complements the statistical analysis by visualizing patient events, such as arrivals, consultation starts and ends, along a timeline. By comparing the dotted charts of days with delays to those without delays, we identify outliers with overly lengthy waiting times and pinpoint operational inefficiencies. The charts reveal patterns such as clustered arrivals, delayed consultation starts, and prolonged consultations, which highlights the areas for improvement. Specifically, PAD shows clusters that indicate peak times; high CIV shows irregular consultation spacing; and high PCTR is observable when prolonged consultation occurs, which causes cumulative delays throughout the day.

IV. TO-BE MODELING

The to-be phase corresponds to process enhancement in the process mining lifecycle. Based on the dominant delay mechanisms diagnosed in the as-is phase (RQ2), we design scheduling interventions and evaluate them using a data-driven discrete-event simulation model whose structure and parameters are calibrated from outpatient event logs (RQ3). This enables realistic what-if testing of appointment policies before implementation.

A. SCENARIO DEVELOPMENT

Three what-if scenarios are developed to address the problems identified in the as-is phase. Scenario 1 proposes increasing the time interval between two consecutive appointments by applying a small buffer (e.g., adding 1 minute to the interval between scheduled times), to reduce the risk of cascading delays throughout the day. For example, appointments originally scheduled at 9:00, 9:05, and 9:10 would be rescheduled to 9:00, 9:06, and 9:12, respectively. The 1-minute and 2-minute buffers were selected as minimal and operationally feasible adjustments rather than fixed rules derived from hospital policy. Because the outpatient schedules in the studied setting were already dense, larger buffers were likely to reduce session capacity more substantially, while smaller increments allowed us to test whether prolonged-consultation-driven delays could be absorbed with limited disruption. Therefore, these values were treated as experimental micro-adjustments for PCTR-dominant cases.

Scenario 2 adjusts specific appointment times to allow flexibility for prolonged consultations. Scenario 3 groups multiple appointment times into averaged time slots to smooth out peak times and improve resource utilization. These scenarios aim to reduce high PAD, address CIV variability, and limit the impact on PCTR. Fig. 3 shows the scenarios.

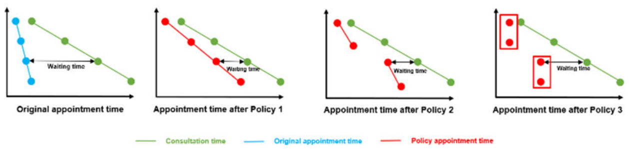


FIGURE 3. **Visualization of different scenarios.**

B. SIMULATION MODELING (DATA-DRIVEN PROCESS SIMULATION; PROCESS ENHANCEMENT; RQ3)

The simulation model was developed using a process-based discrete-event simulation framework. Unlike traditional simulations that often rely on manual parameter assumptions, our model adopts a Data-Driven Process Simulation (DDPS) approach, where the model structure and parameters are directly derived from event logs.

1. Resource and entity modeling: The simulator initializes hospital resources by mapping medical staff (doctors and nurses) to resource objects with capacity constraints. These constraints are based on historical schedules extracted from logs, ensuring that resource availability in the simulation reflects observed real-world shifts. Patients are modeled as active entities that traverse the system, requesting these resources at each stage of their care pathway.

2. Process flow and routing: Process variants correspond to trace types (unique event sequences) mined from the event log. Routing in the simulation follows an empirical model: each patient is assigned a trace type with probability proportional to its observed frequency in the full event log.

3. Stochastic arrival and service times: To reflect real-world variability, the model employs stochastic generation for key time variables:

- Patient arrivals: Arrival-time deviations from the schedule are generated from a (truncated) distribution fitted to observed schedule–arrival offsets, capturing patterns of early arrivals, punctuality, and lateness while avoiding unrealistic extremes.

- Service times: Consultation durations are sampled from physician-specific (empirical/parametric) distributions fitted to historical consultation-duration data.

4. Queue discipline: Patient queues are managed using a priority-based logic. Among clinically-ready patients, the physician serves patients in non-preemptive order of scheduled appointment time; late arrivals join the queue upon clinical check-in, while early arrivals wait until readiness.

C. EVALUATION (MODEL VALIDATION AND WHAT-IF EVALUATION; RQ3)

The simulation model is evaluated using two key performance indicators (KPIs): waiting time (KPI1) and total cycle time (KPI2), both of which are critical indicators of patient experience and efficiency. Waiting time (KPI1) encompasses both RCT and ACT, providing a comprehensive measure of delays attributable to hospital inefficiencies. KPI1 and KPI2 are measured by Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) by comparing the actual and simulated values, with a target MAPE below 10% for high competence. Additionally, as waiting time follows normal distribution, t-tests are also performed to confirm whether there is a significant difference between the actual and simulated values.

D. SYSTEM DEVELOPMENT

We developed MedProSim, a web-based tool for process diagnosis and simulation. MedProSim is implemented as a Flask-based web application, using Python libraries for data handling and visualization. The system adopts a modular architecture that separates data processing, modeling, and execution logic, and consists of three core components:

1. Data preprocessing module: This module automates the cleaning and standardization of raw electronic health record (EHR) event logs. It executes sequential logic rules to correct timestamp inconsistencies—such as outpatient event-order violations (e.g., consultation start recorded before clinical check-in/clinical readiness, or duplicated/overlapping timestamps)—and filters outliers in consultation durations using statistical thresholds (e.g., interquartile range). The module provides an interactive interface, allowing users to apply specific preprocessing filters to ensure data quality before analysis.
2. Parameter extraction & modeling module: To generate a simulation model of the hospital operations, this module analyzes historical event logs to extract essential simulation parameters. It automatically identifies process variants (distinct patient pathways), reconstructs resource schedules (doctor availability based on historical activity logs), and fits service time distributions for clinical activities. This automated extraction ensures that the simulation model reflects the stochastic nature of the real-world environment.

TABLE 1. Event log example.

Arrival (kiosk)	Registration	Consultation start	Consultation end	Appointment	Doctor	Department	Patient	Age
2023-01-18 09:14:30	2023-01-18 09:14:30	2023-01-18 09:20:12	2023-01-18 09:14:30	2023-01-18 09:23:25	X	Pulmonology	201	53
2023-01-18 09:21:46	2023-01-18 09:21:46	2023-01-18 09:22:33	2023-01-18 10:02:30	2023-01-18 09:41:30	X	Pulmonology	202	57
2023-01-18 09:43:43	2023-01-18 09:43:43	2023-01-18 10:02:30	2023-01-18 10:07:57	2023-01-18 09:47:00	Z	Pulmonology	203	62
2023-01-18 09:56:45	2023-01-18 09:56:45	2023-01-18 10:10:21	2023-01-18 10:15:25	2023-01-18 09:56:00	Z	Pulmonology	204	46
2023-01-18 10:25:21	2023-01-18 10:28:00	2023-01-18 10:48:49	2023-01-18 10:52:04	2023-01-18 10:41:00	Y	Pulmonology	205	38

TABLE 2. Descriptive statistics of two departments.

Department	Group	Count	Waiting time				
			Mean	Median	Std	Min	Max
Rheumatology	1	906	18.28	15.33	14.26	0.03	102.15
	2	186	24.1	22.7	14.35	0.03	63.38
	3	4,577	16.85	13.03	13.92	0.03	96.72
Pulmonology	1	1,609	18.59	14.43	16.45	0.017	116.72
	2	104	16.75	12.59	14.20	0.13	74.48
	3	6,115	12.97	9.55	11.81	0.017	73.98

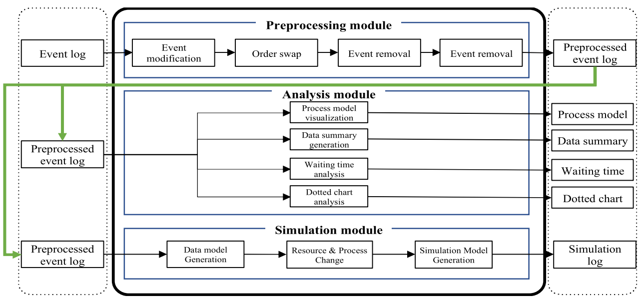


FIGURE 4. System architecture of MedProSim.

3. Simulation engine: The core engine, built on a discrete-event simulation framework, executes the simulation based on the extracted parameters. It dynamically integrates patient flows, resource constraints, and stochastic time variables to replicate daily clinic operations, allowing for the evaluation of various "what-if" scenarios.

V. CASE STUDY

A. DATA DESCRIPTION

Outpatient data was collected from the Electronic Health Record (EHR) system of a tertiary university hospital in Korea, covering January 1st to August 31st of 2023. Among the multiple departments, rheumatology and pulmonology departments are selected due to their distinct operational characteristics. The rheumatology department has straightforward procedures while the pulmonology department includes various preparatory tests, such as blood sampling, which often lead to longer waiting times and more complex patient flows. The event log has 13 activities and includes attributes such as completion times, resources, departments, patient types, and appointment. Table. 1 shows an example event log.

B. DATA PREPROCESSING

To ensure data accuracy, the raw event log has undergone extensive preprocessing, including modifications of activity labels and timestamps. For instance, activities originally labeled "First Order" has been renamed as "Scheduled Prescription" to represent situations where physicians pre-authorized tests or prescriptions before consultations. This adjustment consolidated patient interactions into a single visit by allowing tests to be scheduled in advance, reducing the need for multiple consultations.

Additionally, timestamps that were too close to each other has been adjusted to reflect the actual sequence of activities. In addition, duplicate arrival records have been removed. Lastly, records missing essential information, such as consultation start times, or those showing illogical sequences has also been excluded.

C. DEFINING WAITING TIMES

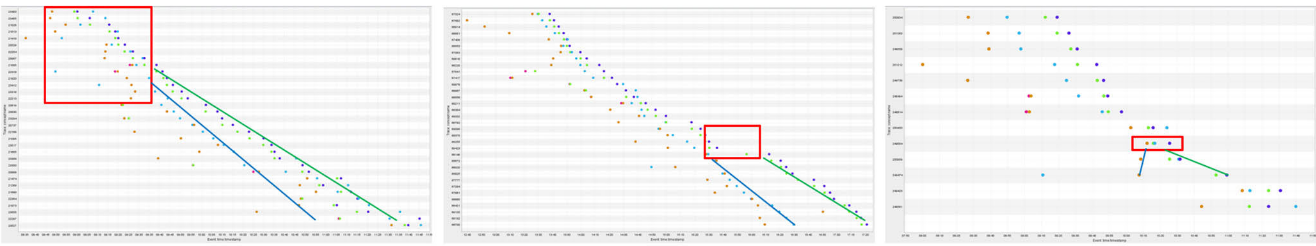
Patients are categorized into three groups based on their appointment and arrival times, as well as registration times. Descriptive statistics are computed for each group to analyze waiting times across rheumatology and pulmonology in Table. 2. Groups 1 and 2 use RCT, while Group 3 uses ACT. In rheumatology, Group 1 had an average waiting time of 36.85 minutes, and Group 2 showed a more consistent pattern with a mean of 27.62 minutes. In pulmonology, Group 3 patients had the shortest average waiting time at 12.97 minutes, showing effective scheduling, while Group 1 patients show the longest waiting.

D. PERFORMANCE ANALYSIS

Dotted chart analysis (Fig. 5) is used as a diagnostic visualization of outpatient flow directly from the event log. The

TABLE 3. T-test results for three physicians in pulmonology.

Department	Physician	Indicator	T-value	p-value
Pulmonology	X	PAD	2.42	0.017
		CIV	0.48	0.633
		PCTR	3.09	0.0028
	Y	PAD	0.63	0.529
		CIV	-3.14	0.002
		PCTR	2.06	0.043
	Z	PAD	-0.28	0.775
		CIV	0.94	0.348
		PCTR	2.29	0.024



2023-01-18 (Physician X) **2023-02-21 (Physician Y)** **2023-05-30 (Physician Z)**

FIGURE 5. Dotted chart for three physicians in pulmonology.

x-axis represents the time of day (e.g., 09:00–18:00), and the y-axis lists individual patient cases ordered by their arrival (or case start) time. Each dot corresponds to a timestamped event recorded in the outpatient event log—clinical check-in (clinical readiness) and consultation start (and other event types if applicable, as indicated in the legend). By reading dots horizontally within a case and vertically across cases, the figure reveals how patients progress through key timestamps over the clinic session. A near straight diagonal trend in consultation-start dots indicates a stable, FIFO-like flow, whereas systematic deviations (e.g., flattening or rightward drift over time) indicate the accumulation of delay and increasing congestion.

Fig. 5 also provides intuitive visual signatures that correspond to the three delay indicators computed from the same event log (PAD, CIV, and PCTR), thereby offering qualitative corroboration for the indicator-based diagnosis. High PAD (peak arrival clustering) is suggested when many cases show tightly aligned readiness-related events within narrow time windows (i.e., visually dense vertical clustering of early-session dots), consistent with clustered arrivals and downstream queueing. High CIV (irregular consultation pacing) is suggested by conspicuous gaps and uneven spacing between successive consultation-start dots for the same physician, reflecting intermittent idle periods and variability in start-to-start pacing. High PCTR (prolonged-consultation–driven delay propagation) is suggested by a progressive rightward drift of consultation-start dots over the session (i.e., consultations starting increasingly later as time advances), indicating cascading delay consistent with long-service-time effects rather than isolated idle gaps. Accordingly, Fig. 5 supports scenario selection by linking dominant visual/quantitative mechanisms to targeted interventions: PAD-like clustering motivates schedule smoothing (Scenario 2), CIV-like irregular pacing motivates grouping into blocks (Scenario 3), and PCTR-like delay propagation motivates buffering between appointments (Scenario 1).

E. EXPERIMENTAL RESULTS

1) MODEL VALIDATION

The simulation model's accuracy was validated by comparing the observed and simulated logs in terms of average waiting time and total cycle time on three selected dates (January 18, February 21, and May 30). For each date, we performed 100 independent simulation replications with different random seeds and summarized the results using the mean (and variability where appropriate) across replications. These dates were selected via a pattern-driven rationale: they constitute clear, prototypical instances in which the dominant delay patterns targeted in this study—peak arrival clustering (high PAD), irregular consultation pacing (high CIV), and prolonged consultations (high PCTR)—are distinctly

TABLE 4. Evaluation results.

Date	Runs: 100 times (minutes)	Average waiting time		Cycle time	
		Logs	Simulation	Logs	Simulation
1/18	Average	12.0	12.0	27.0	26.3
	t-statistics (p-value)	0.00 (1.0)		-1.56 (0.136)	
	MAPE	3.36		3.67	
2/21	Average	24.4	24.2	43.01	42.7
	t-statistics (p-value)	0.8 (0.433)		-1.15 (0.264)	
	MAPE	2.47%		1.65%	
5/30	Average	20.11	20.9	56.7	56.0
	t-statistics (p-value)	1.37 (0.196)		-1.34 (0.188)	
	MAPE	3.37%		7.79%	

TABLE 5. Paired comparison of waiting time measured by ACT (proposed) and DTD (baseline) under the policy scenarios.

Physician	Indicator	Date	Scenario -parameters	Metric	Initial waiting time (min)	Adjusted waiting time (min)	Improvement (%)
X	PAD	1/18	Scenario 2 – 09:30 am, 2 min delay	ACT	10.8	6.4	40.7
				DTD	21.75	18.18	16.4
X	PCTR	2/21	Scenario 1 – 2 min delay	ACT	22	15.96	27.5
				DTD	26.47	23.56	10.9
Y	CIV	2/21	Scenario 3 – 3 appointment times	ACT	24.49	14.33	41.5
				DTD	35.18	34.67	1.4
Z	PCTR	5/30	Scenario 1 – 1 min delay	ACT	20.16	13.19	34.6
				DTD	39.58	37.29	5.8

observable in the event log, enabling an interpretable validation rather than an arbitrary choice of days.

For January 18, the average waiting time in both the observed and simulated logs was 12.0 minutes, with a t-statistic of 0.00 and a p-value of 1.0, indicating no statistically meaningful difference in average waiting time for this validation case. The model also achieved a low error in total cycle time (e.g., MAPE = 3.36%). Similar validation outcomes for February 21 and May 30 further confirmed that the simulation model closely approximates the observed patient flow on days characterized by different dominant delay mechanisms. Table 4 summarizes the evaluation results for all three validation dates.

2) WHAT-IF ANALYSIS FOR THREE PHYSICIANS

We conducted a what-if analysis on three pulmonology physicians (X, Y, and Z) to evaluate the effectiveness of targeted scheduling adjustments under distinct dominant delay mechanisms diagnosed from the event log: peak arrival clustering (PAD), irregular consultation pacing (CIV), and prolonged consultation times (PCTR). The physician–day cases reported in Table 5 were selected as representative examples to illustrate that there is no one-size-fits-all solution; the most effective policy depends on the dominant mechanism on a given day. Notably, we include multiple PCTR-dominant cases to show that even the same mechanism can require different buffering settings and can yield different operational trade-offs across physicians and clinic days.

After selecting these physician–day cases, we assessed the impact of each scheduling scenario on the waiting-time KPI that is most relevant to the corresponding physician–day timeline, as defined in Fig. 2. Specifically, we quantified changes in appointment-related delay using our proposed measures (ACT/CCT) and summarized baseline versus policy outcomes in Table 5. To connect our findings to existing outpatient evidence and to clarify how conventional reporting would reflect these improvements, we also report paired outcomes using Door-to-Doctor time (DTD) as a baseline metric. All simulation-based estimates are computed from 100 independent replications with different random seeds and are summarized as averages (and variability where appropriate).

a: COMPARISON AGAINST THE CONVENTIONAL BASELINE (DTD) AND IMPLICATIONS FOR METRIC CHOICE (TABLE 5)

Table 5 reports the proposed waiting-time measures alongside DTD for each physician–day case. In several cases, the improvements measured by the proposed appointment-related KPI are substantially larger than those observed under DTD (e.g., Physician Y: −41.5% under the proposed measure vs. −1.4% under DTD). This discrepancy is expected because DTD aggregates patient arrival

TABLE 6. Impacts of the policy scenarios on throughput and average consultation time per patient.

Physician	Indicator	Date	No. Patients (before)	Adjusted No. Patients (after)	Avg consult time (min, before)	Avg consult time (min, after)
X	PAD	1/18	39	33	3.70	9.34
X	PCTR	2/21	34	29	5.90	7.50
Y	CIV	2/21	36	34	6.77	8.34
Z	PCTR	5/30	27	24	7.15	7.20

behavior (including voluntary early arrivals) with clinic-side delays, whereas ACT/CCT are designed to better isolate clinic-controllable delay and schedule adherence. As a result, DTD-only reporting may understate improvements that primarily enhance schedule compliance and internal clinic performance. The paired reporting therefore provides a more transparent interpretation: the proposed measures reveal the magnitude of clinic-controllable improvement, while DTD reflects a broader end-to-end experience that can be influenced by arrival behavior.

b: IMPACT ON PATIENT THROUGHPUT AND CONSULTATION DURATION (TABLE 6)

Beyond waiting-time outcomes, we quantified operational impacts to make trade-offs explicit, focusing on (i) session throughput (the number of consultations completed within the evaluated clinic session window) and (ii) average consultation time per completed patient under baseline versus each policy (Table 6). Throughput decreased after policy application in multiple cases (X, 1/18: 39 → 33; X, 2/21: 34 → 29; Y, 2/21: 36 → 34; Z, 5/30: 27 → 24). In parallel, the average consultation time per completed patient increased or remained similar (X, 1/18: 3.70 → 9.34 min; X, 2/21: 5.90 → 7.50 min; Y, 2/21: 6.77 → 8.34 min; Z, 5/30: 7.15 → 7.20 min). These averages should not be interpreted as the policy directly changing clinicians' service times; rather, they reflect simulation outputs for the subset of patients who complete consultations within a fixed session window and inherent stochastic variability under revised scheduling constraints. Importantly, the magnitude of the trade-off is context dependent: for example, Physician Y achieved a large reduction in the proposed waiting-time KPI with only a modest throughput decrease (36 → 34), whereas Physician X's PAD-dominant day exhibited a larger throughput decrease (39 → 33). Taken together, the waiting-time improvements (Table 5) and the throughput/consultation-duration impacts (Table 6) provide a case-specific basis for balancing patient experience (waiting and schedule adherence) against capacity targets when considering appointment policy changes.

VI. DISCUSSION

This study demonstrates that targeted, mechanism-informed scheduling adjustments can meaningfully reduce outpatient waiting-time–related delays and improve operational performance in the pulmonology clinic. By diagnosing dominant delay mechanisms from event logs (PAD, CIV, and PCTR) and evaluating corresponding intervention scenarios via simulation, we show that relatively minor appointment-policy changes—such as smoothing peak-hour schedules, introducing small buffers, or grouping appointments—can improve patient flow and reduce clinic-controllable delays. Importantly, the results also reinforce that there is no one-size-fits-all intervention: effectiveness depends on the dominant delay mechanism and the physician–day context, and even the same mechanism (e.g., PCTR) can require different parameter settings across physicians and days.

A. POLICY EFFECTS ON THE PROPOSED WAITING-TIME KPIS (TABLE 5)

Across all evaluated physician–day cases, the targeted scenarios yielded substantial reductions in the proposed waiting-time KPIs, consistent with improved schedule adherence and/or reduced clinic-attributable waiting under the diagnosed dominant mechanisms. For the PAD-dominant case (Physician X, Jan 18), smoothing clustered arrivals via an incremental delay starting at 9:30 AM (Scenario 2) reduced the proposed waiting-time KPI from 10.8 to 6.4 minutes (−40.7%), indicating that modest schedule shifts can decompress peak arrival loads. For PCTR-dominant cases, buffering proved effective: adding a 2-minute buffer (Physician X, Feb 21; Scenario 1) reduced the proposed waiting-time KPI from 22.0 to 15.96 minutes (−27.5%), and a 1-minute buffer (Physician Z, May 30; Scenario 1) reduced it from 20.16 to 13.19 minutes (−34.6%). These findings support the interpretation that small buffers can absorb variability introduced by prolonged consultations and prevent cascading delays. The results also suggest that buffering was effective in both PCTR-dominant cases, but that the preferable setting was context dependent: a 2-minute buffer was more effective for Physician X, whereas a 1-minute buffer was sufficient for Physician Z. For the CIV-dominant case (Physician Y, Feb 21), grouping appointments into blocks (Scenario 3) reduced the proposed waiting-time KPI from 24.49 to 14.33 minutes (−41.5%), suggesting that grouping can stabilize pacing and mitigate variability-driven gaps more efficiently than uniform buffering in certain contexts. Collectively, Table 5 illustrates that mechanism-targeted policies produce the largest gains when the intervention is aligned with the dominant diagnostic indicator.

B. COMPARISON AGAINST THE CONVENTIONAL BASELINE (DTD) AND IMPLICATIONS FOR METRIC CHOICE (TABLE 5)

A key contribution of this study is demonstrating how conclusions about improvement effectiveness can depend strongly on the waiting-time metric used. While Door-to-Doctor time (DTD) is widely reported in outpatient studies, it aggregates patient arrival behavior (including voluntary early arrivals) with clinic-side delays. As a result, DTD can understate improvements that primarily enhance schedule adherence and internal process performance. The paired comparison in Table 5 shows that the proposed appointment-related KPI improvements are consistently larger than those observed under DTD for the same interventions (e.g., Physician Y: -41.5% under the proposed measure vs. -1.4% under DTD). This discrepancy is expected: an intervention that reduces appointment-based delay may substantially improve clinic-controllable performance while leaving the DTD metric relatively unchanged if the patient population continues to arrive early or variably. Therefore, relying solely on DTD could lead decision makers to underestimate the effectiveness of valid process improvements. In contrast, ACT/CCT provide more targeted evidence for evaluating appointment policies intended to reduce clinic-controllable delays and improve schedule adherence, while DTD remains useful as a broader end-to-end measure that reflects both clinic-side and patient-side factors.

C. IMPACT ON PATIENT THROUGHPUT AND CONSULTATION DURATION (TABLE 6)

Beyond waiting-time outcomes, the scenarios affected operational capacity and time spent per patient, highlighting explicit trade-offs. As summarized in Table 6, throughput (completed consultations within the evaluated session window) decreased to varying degrees after policy application (X, 1/18: 39→33; X, 2/21: 34→29; Y, 2/21: 36→34; Z, 5/30: 27→24). In parallel, the average consultation time per completed patient increased or remained similar across cases. These patterns indicate that buffering or smoothing policies can reduce clinic-controllable delays and stabilize schedules, but may also reduce the number of patients completed within a fixed session window under certain conditions.

Crucially, the concurrent increase in average consultation time per completed patient should not be interpreted as the policy directly changing clinicians' service times. Rather, it reflects simulation outputs computed over the subset of completed cases within the fixed session window and inherent stochastic variability under revised scheduling constraints. The case-level results underscore that these trade-offs are context dependent. For example, Physician Y achieved a large reduction in the proposed waiting-time KPI with only a modest throughput decrease (36→34, -5.5%), suggesting that variability-driven delays can be mitigated efficiently through process-oriented policies (e.g., grouping) without substantial volume loss. By contrast, Physician X's PAD-dominant day showed a larger throughput decrease (39→33, -15.4%) alongside a larger change in average consultation time, consistent with a more time-constrained baseline schedule on that day. Overall, jointly reporting appointment-related measures alongside DTD (Table 5) and operational impacts (Table 6) provides a transparent basis for balancing patient experience (waiting and schedule adherence) against capacity targets when considering appointment-policy changes.

D. TOOL DIFFERENTIATION AND PRACTICAL SCALABILITY

MedProSim should be understood as a specialized data-driven decision-support tool rather than a general-purpose DES environment. Unlike widely used simulation platforms such as Arena, AnyLogic, FlexSim, or ProModel, which often require substantial manual model construction and parameter specification, MedProSim integrates event-log preprocessing, automatic extraction of process variants and physician schedules, service-time distribution fitting, and scenario-based simulation within a single web-based workflow. This design directly links diagnosis and improvement evaluation around the proposed waiting-time KPIs and delay indicators, thereby reducing the modeling burden for outpatient analysis. In addition, because the model structure and parameters are recalibrated from updated event logs, the framework can be reused across different physician-day cases and potentially across departments without rebuilding the simulation logic from scratch, which supports practical scalability. Although the current study evaluates scenarios retrospectively, the same architecture has the potential to support near-real-time or periodic reanalysis when updated event logs become available, enabling more responsive adjustment of appointment policies in practice.

E. LIMITATIONS AND FUTURE WORK

This study has several limitations that motivate future work. First, the case study focuses on a limited set of physicians and departments, which may constrain generalizability across different specialties, patient populations, and operational regimes. Second, although the simulation is calibrated from observed event logs and validated on representative physician–day patterns, simulation-based conclusions depend on modeling assumptions and available data granularity. Third, while we quantify throughput and consultation-duration changes, we do not explicitly model downstream consequences such as staffing constraints, overtime, patient satisfaction outcomes, or hospital revenue implications—factors that can materially affect feasibility and decision-making.

VII. CONCLUSION

This paper presents a framework for reducing outpatient waiting times using a two-phased approach: an as-is phase to diagnose current delays and a to-be phase to propose operational improvements through simulation. The as-is phase defines waiting times based on patient arrival and appointment behaviors and uses key indicators and dotted chart analysis to identify delay sources. The to-be phase develops scenarios for each indicator and simulates changes to optimize patient flow. Applying this framework to a Korean tertiary hospital dataset showed significant reductions in waiting times and improved patient flow efficiency.

The study makes three main contributions: first, by defining distinct waiting times, it enables a clearer understanding of delay sources, helping to identify areas needing improvement and supporting effective interventions. Second, it introduces multiple indicators for a precise assessment of hospital performance, pinpointing where changes are essential to reduce inefficiencies. Third, MedProSim, a web-based decision-support tool, enables hospital administrators to make data-driven decisions by testing process changes before implementation. Future work will expand the study to departments like radiology and emergency to test the framework's adaptability. Additionally, economic analysis will assess cost-effectiveness, and the simulation model will consider unpredictable factors like patient no-shows and emergencies to create a more flexible tool for hospital operations.

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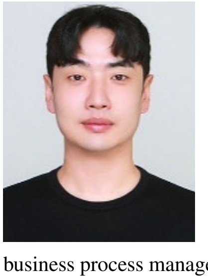

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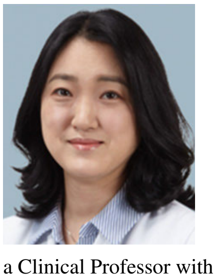

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