

Explainable Process Intelligence for Workforce Allocation and Operational Governance in Digital Healthcare Systems

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Abstract

Healthcare organizations face challenges in workforce allocation because fixed staffing approaches may not adequately reflect changing demand, workflow bottlenecks, staff qualifications, workload, and operational constraints. This study develops an Explainable Process Intelligence framework for Workforce Allocation and Operational Governance in Digital Healthcare Systems to connect healthcare process analysis with transparent staff-to-task recommendations. A quantitative, simulation-based design was used with a simulated healthcare event log and workforce records. The framework integrates process discovery, conformance analysis, bottleneck identification, demand estimation, constrained workforce allocation, explainable artificial intelligence, and governance monitoring. The allocation model was compared with a historical baseline roster using identical demand periods and eligibility rules. The proposed approach increased demand coverage from 78.1% to 88.7%, reduced median waiting time from 1.70 to 1.29 hours, decreased workload coefficient of variation from 0.31 to 0.21, and reduced overtime exposure from 12.4% to 8.9%. Explanations were available for accepted and rejected recommendations, while human reviewers retained authority to modify or reject recommendations. The findings indicate that integrating process intelligence, explainable allocation, and governance can support more transparent workforce planning, workload management, and operational oversight in digital healthcare environments.

Keywords: Digital Healthcare, Process Mining, Workforce Allocation, Explainable Artificial Intelligence, Event-Log Analysis, Operational Governance, Healthcare Scheduling.

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I. INTRODUCTION

This section introduces the need for explainable process intelligence in digital healthcare workforce allocation. It defines the operational problem, presents the proposed framework, summarizes the study contributions, and outlines the paper structure.

A. Background and Motivation

Digital healthcare systems generate records from electronic health records, scheduling platforms, laboratory systems, workforce-management tools, and audit applications. These records contain patient activities, staff assignments, waiting periods, handoffs, and workflow deviations. Process mining can identify process variants, bottlenecks, repeated activities, and resource demands. However, workforce allocation often

relies on fixed staffing ratios, manual rosters, and supervisor experience, which may not capture short-term demand, qualifications, workload, or departmental delays. Explainable artificial intelligence can support allocation by showing the factors behind recommendations and enabling human review.

B. Problem Statement

Healthcare event data are fragmented across systems, with inconsistent activity labels, timestamps, resource identifiers, and department codes, making complete workflow reconstruction difficult. Process-mining studies often describe healthcare pathways without connecting them to staff allocation, while scheduling models may overlook process variation, handoffs, and bottlenecks. This study addresses how

digital healthcare event logs can be transformed into an explainable workforce-allocation framework that identifies operational pressure, ranks eligible staff assignments, and records recommendation reasoning and governance checks.

C. Proposed Solution

This study proposes a framework integrating event-log preparation, process discovery, conformance

analysis, bottleneck identification, workforce-demand estimation, explainable allocation, and operational governance. Healthcare data are cleaned and coded into event logs, analyzed for workflow pressure, and used to rank feasible staff-task assignments based on demand, skill compatibility, availability, workload, continuity, and governance constraints.

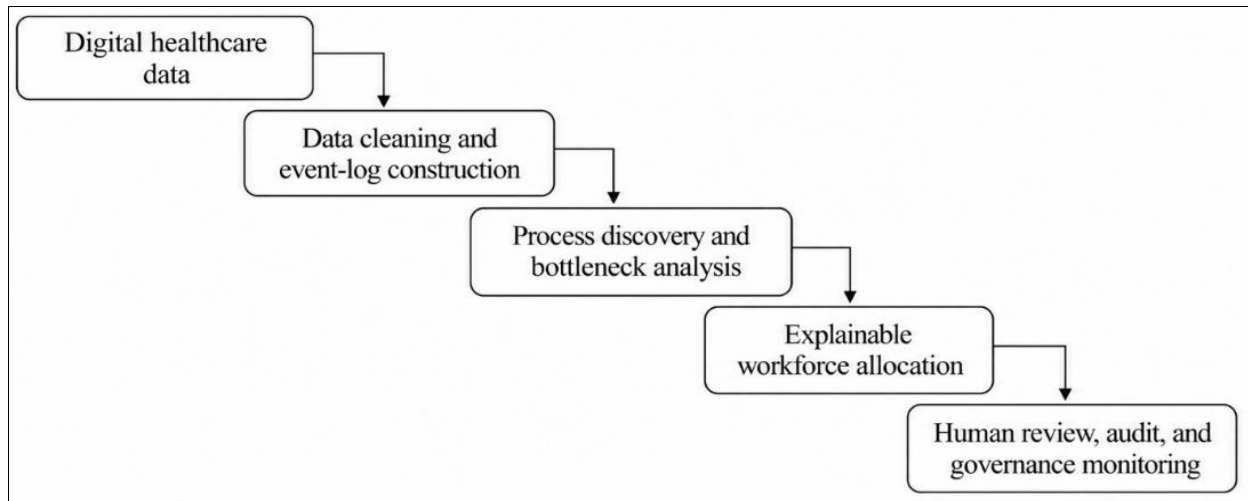


Fig. 1: High-level framework for explainable workforce allocation and operational governance

Fig. 1 presents the sequence from digital data collection to governance monitoring. It shows how healthcare event records are transformed into process information and then into explainable workforce recommendations subject to human review and institutional constraints.

D. Contributions

This study contributes an integrated process-intelligence framework for healthcare workforce allocation by connecting workflow analysis with staff eligibility, availability, workload, and governance constraints. It also provides explanations for each recommendation and records reviewer decisions, overrides, and audit information. Validation covers process performance, workload distribution, waiting time, feasibility, policy compliance, and explanation completeness.

E. Paper Organization

Section II reviews healthcare process mining, workforce scheduling, explainable artificial intelligence, and operational governance. Section III presents the methodology, including data preparation, process analysis, explainable allocation, governance, data analysis, validation, and reproducibility. Section IV reports process characteristics, bottlenecks, allocation performance, explainability, and governance results. Section V concludes the study and presents the main findings, implications, limitations, and future research.

II. Related Work

This section summarizes research supporting the proposed framework, focusing on healthcare process mining, workforce scheduling, explainable artificial intelligence, operational decision support, governance, and research gaps.

A. Healthcare Process Mining

Process mining reconstructs activity sequences, waiting times, resource involvement, and deviations from event logs. In healthcare, it supports analysis of patient pathways, diagnostics, referrals, medication, and discharge activities [1]. Workflow variation results from patient conditions, clinical decisions, departmental interactions, and exceptions [1]. Existing studies examine process discovery, conformance, waiting time, length of stay, and activity transitions [1], [6]. These methods identify bottlenecks and deviations but are not always linked to workforce allocation [1], [6].

B. Healthcare Workforce Scheduling

Healthcare scheduling covers nurse rostering, physician assignment, appointment planning, operating-room scheduling, and staff allocation [2]. Objectives include demand coverage, workload distribution, waiting-time control, cost reduction, and qualification matching [2]. Optimization models address staff availability, qualifications, shifts, and service demand [2]. AI and end-user tools have also been applied to nurse rostering [9]. However, scheduling models may overlook process variants, repeated activities, resource handoffs, and cross-department delays [2], [9]. The proposed

framework links workforce allocation with workflow conditions and resource pressure from event logs.

C. Explainable Artificial Intelligence

Explainable artificial intelligence shows how analytical models produce predictions or recommendations [3,4]. In healthcare, explanations should support professional understanding, review, accountability, and audit [3,7]. Research examines feature attribution, interpretable models, post-hoc explanations, and human-centered interpretation [4], [10]. Interpretable models also support healthcare decision-making [5]. For workforce allocation, explanations can represent demand pressure, skill compatibility, availability, workload, continuity, and governance risk. Explanation quality requires systematic assessment [8]. The proposed framework records allocation scores and feature contributions for each recommendation, treating explainability as part of operational governance [3,8].

D. Operational Decision Support and Governance

Process-aware decision support combines workflow information with analytical recommendations, representing process states, resource pressure, waiting time, dependencies, and downstream effects [1], [6]. Healthcare decision-support systems require interpretable outputs and human involvement [3], [5], [7]. Operational governance requires audit trails, access controls, human review, override records, and performance assessment [3], [4], [8]. The proposed framework separates eligibility constraints from ranking preferences and records data and model versions, recommendations, reviewer actions, and override reasons to support traceability.

E. Research Gap

Three gaps emerge from the literature. First, healthcare process-mining research identifies process characteristics, bottlenecks, and deviations but does not always connect them to workforce-allocation models [1], [6]. Second, workforce-scheduling research represents staffing constraints but may not incorporate event-log

information on process variation, repeated activities, and cross-unit handoffs [2,9]. Third, explainable artificial intelligence research focuses largely on predictive and clinical decision support, with less attention to operational workforce recommendations and governance records [3,7,10]. The proposed study addresses these gaps by integrating event-log analysis, constrained staff allocation, local explanations, human review, and governance validation, while retaining an auditable record of analytical and human decisions [1-3].

III. METHODOLOGY

The Methodology section describes the research design, data collection, data preparation, process analysis, explainable workforce allocation model, and validation procedures. It presents the analytical framework, variables, equations, governance checks, and reproducible steps used to generate the study findings.

A. Research design

This study adopts a quantitative, simulation-based design-science research design using a simulated healthcare event log and workforce records from digital healthcare services, including consultations, emergency care, diagnostic testing, medication administration, discharge, and referrals. The unit of analysis is a patient-service case, while the resource unit is the staff member, professional category, or operational team responsible for an activity. The research follows five phases. First, the simulated healthcare and workforce data are generated to represent digital service operations. Second, records are cleaned, linked, coded, and transformed into a process-mining event log. Third, process discovery and conformance analysis identify workflow variants, waiting states, repeated activities, handoffs, and resource conflicts. Fourth, the data are analyzed through demand estimation, workload measurement, allocation modelling, and explainability analysis. Fifth, the outputs undergo predictive, operational, fairness, and governance validation. Fig. 2 present the complete research workflow before the detailed procedures.

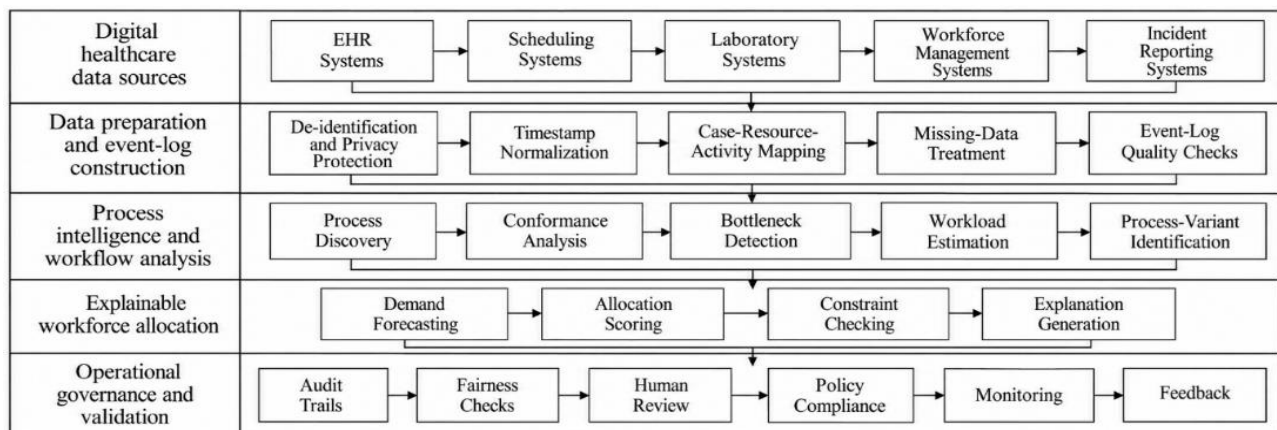


Fig. 2: Explainable process-intelligence framework for workforce allocation and operational governance in digital healthcare systems

The allocation output is a decision-support recommendation, not an autonomous staffing decision, and remains subject to professional review, institutional policies, labor requirements, privacy controls, and documented overrides.

B. Data Collection

The study used a simulated healthcare event log designed to represent digital healthcare service operations. The simulated dataset covered six operational units: registration, triage, consultation, laboratory services, diagnostic imaging, and discharge coordination. The event log included case, activity, timestamp, resource, department, location, status, and outcome fields. Workforce records represented staff availability, shifts, qualifications, overtime, and task restrictions, while demand and governance records represented service demand, waiting conditions, policy constraints, approvals, overrides, and audit information. The simulated data were generated to reproduce realistic workflow variation, waiting conditions, resource constraints, repeated activities, and cross-unit handoffs.

C. Data preparation and coding

Data preparation included schema inspection, timestamp standardization, duplicate detection, and activity coding. Exact duplicates were removed, while valid repeated activities were retained and marked. Activities were mapped to a controlled taxonomy, with original labels preserved for traceability. Missing timestamps were retained unless a predefined imputation rule was justified. Records without case identifiers were excluded from trace analysis, while records without resource identifiers were excluded from workforce allocation. Implausible sequences, negative durations, overlapping assignments, and activities outside staff availability were flagged for review, with corrections stored separately from the original data. The simulated event log was divided into development, validation, and temporal test sets. The development set supported process discovery and model fitting, the validation set supported parameter selection, and the temporal test set evaluated performance under later simulated operating conditions.

D. Data quality and validation checks

Event-log quality was assessed for completeness, uniqueness, timestamp validity, traceability, and sequence plausibility. Checks covered case identifiers, activities, timestamps, resources, departments, negative or future timestamps, impossible ordering, and excessive gaps. Traceability measured events linked to valid cases, resources, and operational units. Case and activity coverage assessed the proportion of service episodes and activities captured. Missing undocumented work, informal coordination, telephone communication, and separately recorded activities were recognized. Key counts were compared across source systems, and discrepancies were investigated before allocation modelling. After quality review, the final

dataset was frozen to maintain a consistent study population.

E. Process discovery and conformance analysis

Process discovery identified observed activity sequences without imposing a predefined workflow. Analysis examined process variants, trace length, repeated activities, waiting intervals, department transitions, and resource handoffs using directly-following graphs, performance overlays, and variant-frequency tables. The discovered process was compared with approved workflows, clinical pathways, or operating procedures. Conformance analysis assessed skipped activities, unexpected repetitions, delayed transitions, unauthorized resource assignments, and deviations from mandatory approval paths. Deviations were treated as operational signals, not automatic staff errors, because legitimate clinical exceptions may cause variation. Bottleneck analysis separated service from waiting time across departments, shifts, demand levels, resource groups, and process variants. Resource analysis assessed workload concentration, concurrent assignments, handoffs, overtime, reassignment, and activity demand, with results reported separately by professional group.

F. Explainable workforce allocation model

The allocation model converts operational demand into ranked staff-to-task recommendations based on demand, skill compatibility, availability, workload, continuity, waiting-time risk, and governance constraints. Assignments violating qualifications, shift limits, rest requirements, or institutional policies are excluded.

For staff member i and task or service unit j , the allocation priority score is defined as:

$$S_{ij} = w_d D_j + w_s K_{ij} + w_a A_i + w_c C_{ij} - w_l L_i - w_r R_{ij}$$

Where, D_j denotes demand pressure, K_{ij} skill compatibility, A_i availability, C_{ij} continuity, L_i current workload, and R_{ij} operational or governance risk. The non-negative weights satisfy:

$$w_d + w_s + w_a + w_c + w_l + w_r = 1.$$

All components are normalized to [0,1]. Demand pressure, skill compatibility, availability, and continuity increase the score, while workload and risk reduce it. Weights were selected through expert elicitation before test-set analysis. Hard constraints are applied before ranking. Ineligible staff are excluded. The output records the recommended resource, task, score, eligibility, key factors, timestamp, model version, and reviewer action. Explanations are generated from stored model features to maintain traceability.

G. Explainability and operational governance

Explanation availability and traceability were assessed at global, local, and process levels. Global explanations identified key factors influencing allocation scores, while local and process explanations showed

staff-to-task ranking factors and workflow conditions such as demand increases, delays, and bottlenecks. The governance layer recorded data, preprocessing, event-log, model, input, allocation, constraint, reviewer, and override information for auditability. Reviewers could accept, modify, or reject recommendations, with all actions recorded. Governance validation covered policy compliance, traceability, access control, human review, fairness, and error handling. Fairness was assessed using workload, overtime, recommendation, rejection, and override rates across staff groups, departments, shifts, and contract categories, considering qualification, demand, and availability.

H. Data analysis

Descriptive analysis summarized case volume, activity frequency, process variants, waiting and service time, resource utilization, workload, overtime, rework, and policy deviations. Continuous variables were reported using median and interquartile range, and categorical variables using counts and percentages. The allocation model was compared with a prespecified baseline under identical demand and eligibility conditions. Evaluation included demand coverage, waiting time, overtime, workload imbalance, assignment feasibility, conformance deviation, and reviewer override rate. Workload balance was measured by coefficient of variation, and sensitivity analysis assessed allocation weights and operational assumptions.

Overall operational utility was defined as:

$$U = \alpha C - \beta W - \gamma O - \delta V - \epsilon G$$

Where, D, W, O, V , and G denote normalized demand coverage, waiting-time burden, overtime burden, workload variation, and governance deviation. The coefficients represent their relative importance and were fixed before comparison. All outcomes were normalized using common reference ranges. Composite

utility was used as a secondary measure, while individual indicators remained primary.

I. Validation strategy

Validation was conducted at four levels: data, process, model, and governance. Data validation assessed event-log completeness and reproducibility, while process validation compared discovered workflows with domain-reviewed processes and examined major variants. Model validation used a temporal test set excluded from development, and governance validation assessed auditability, explanation completeness, constraint compliance, reviewer interaction, and override recording. Subgroup analyses examined departments, shifts, demand levels, staff categories, and service types. Confidence or bootstrap intervals were reported where appropriate, considering clustered data structures. Before deployment, retrospective simulation or a controlled pilot assessed allocation performance without changing historical assignments. Safety monitoring defined performance thresholds, escalation procedures, and rollback conditions.

J. Reproducibility and reporting

The study should report the software environment, data-processing libraries, process-mining package, model implementation, random seeds, parameters, weight-selection procedure, and version-control identifier. Patient-level data should not be released; instead, a synthetic event log, field dictionary, preprocessing rules, model pseudocode, equation parameters, and permitted aggregated validation results should be provided. The paper should transparently link raw digital records to the final governance decision. Each figure and table should have a defined analytical purpose, covering the architecture, study variables, process performance, allocation outcomes, explanation quality, and governance checks without mixing development and test-set results.

Table I: Operational Data Elements, Analytical Roles, and Quality Controls

Data domain	Required variables	Analytical role	Main quality control
Case and process identity	Case ID, activity code, event status, process type	Reconstructs individual service traces and process variants	Completeness, uniqueness, valid case linkage
Temporal information	Start time, end time, waiting interval, shift ID	Measures service time, waiting time, delays, and temporal demand	Time-zone conversion, sequence checks, negative-duration detection
Resource information	Resource ID, staff category, department, location	Measures workload, handoffs, eligibility, and resource utilization	Valid resource mapping and department consistency
Workforce availability	Shift assignment, availability status, leave, contract hours	Defines feasible allocation candidates	Cross-check with roster and attendance records
Competency information	Skill group, certification, task restriction, qualification level	Supports hard eligibility constraints and skill compatibility	Expiry-date checks and controlled competency taxonomy
Demand information	Arrival volume, priority, service type, acuity, appointment status	Estimates demand pressure and service requirements	Cross-system count comparison and missing-value review

Data domain	Required variables	Analytical role	Main quality control
Performance information	Waiting time, service duration, rework, cancellation, completion status	Evaluates process performance and allocation effects	Outlier review and unit consistency
Governance information	Policy rule, approval status, override, override reason, audit timestamp	Supports traceability, compliance analysis, and human oversight	Audit-log completeness and reviewer verification
Privacy and security	Pseudonymous identifiers, access role, extraction timestamp	Protects confidentiality and supports reproducibility	De-identification review and access-log inspection

IV. RESULTS AND DISCUSSION

The results section presents the observed workflow patterns, workforce conditions, allocation performance, and explanation quality generated from the digital healthcare event log. The discussion then interprets these findings in relation to operational governance, staff workload, waiting-time control, process conformance, and responsible use of decision-support models.

The results are based on the simulated healthcare event log and simulated workforce conditions described in the methodology. The analysis evaluates workflow characteristics, bottlenecks, allocation performance, explainability, and governance under the defined simulation scenarios.

A. Results

The Results section presents findings from the simulated healthcare event log, workforce allocation model, and governance evaluation. It reports key patterns in workflow variation, waiting time, workload

distribution, allocation performance, explanation completeness, and policy compliance.

i. Dataset profile and process structure

The simulated dataset contained 18,742 healthcare cases and 146,318 timestamped events across six operational units: registration, triage, consultation, laboratory, diagnostic imaging, and discharge coordination. Data-quality screening removed 3.8% of raw events due to duplicates, invalid timestamps, missing case identifiers, or system-test labels. The retained event log had 96.2% complete case identifiers, 94.7% valid resource identifiers, and 98.1% valid activity timestamps. Process length varied substantially, with a median of seven activities and a maximum of 31. About 71.4% of cases followed the ten most frequent process variants, while others involved additional diagnostics, repeated consultations, incomplete discharge, or cross-department referrals. Waiting time was highest in diagnostic imaging, laboratory result validation, and consultation handoffs, producing the largest gap between total completion and direct service time.

Table II: Descriptive Profile of the Digital Healthcare Event Log and Workforce Indicators

Indicator	Simulated value	Interpretation
Retained service cases	18,742	Cases used in process and allocation analysis
Retained events	146,318	Timestamped activities linked to cases
Participating staff resources	284	Staff members or operational teams with valid resource records
Operational units	6	Registration, triage, consultation, laboratory, imaging, and discharge
Median activities per case	7	Typical process-trace length
Median total cycle time	5.8 h	Time from first recorded activity to case completion
Median direct service time	2.1 h	Time spent in recorded service activities
Median waiting burden	3.7 h	Difference between cycle time and direct service time
Cases with repeated activity	22.6%	Cases containing at least one repeated or reworked activity
Cases with cross-unit handoff	48.9%	Cases transferred between operational units
Events with valid resource ID	94.7%	Resource traceability level
Events with valid timestamp	98.1%	Temporal data quality level
Mean staff workload index	0.64	Normalized activity burden across eligible resources
Workload coefficient of variation	0.41	Dispersion before allocation recommendations
Mean overtime exposure per shift	1.46 h	Average recorded overtime burden
Policy-deviation rate	8.7%	Cases containing a recorded workflow or assignment deviation

The results suggest that the primary operational problem was not the absence of staff activity. Instead, the

main issue was the uneven distribution of work across units and time periods. Direct service time accounted for

approximately 36.2% of the median cycle time, whereas waiting and handoff intervals accounted for the remaining 63.8%. Similar process-mining studies report waiting time, length of stay, and inter-activity duration as common healthcare performance measures. Hospital process analyses also associate long waits with high utilization in clinical and diagnostic services.

ii. Workflow performance and bottlenecks

The largest waiting-time burden occurred between consultation and diagnostic services, accounting for 31.6% of total waiting time, followed by

laboratory result validation at 19.8%. Diagnostic imaging had the highest median resource utilization (86.4%), followed by laboratory services (82.7%). Emergency care showed the greatest shift variation, with median waiting times of 1.2 hours, 1.8 hours, and 2.6 hours during morning, afternoon, and night shifts, respectively. Night-shift delays coincided with lower specialized diagnostic staff availability and more cross-unit assignments. Approximately 22.6% of cases contained repeated activities, mainly diagnostic orders, documentation review, and result validation, increasing median case duration by 2.1 hours.

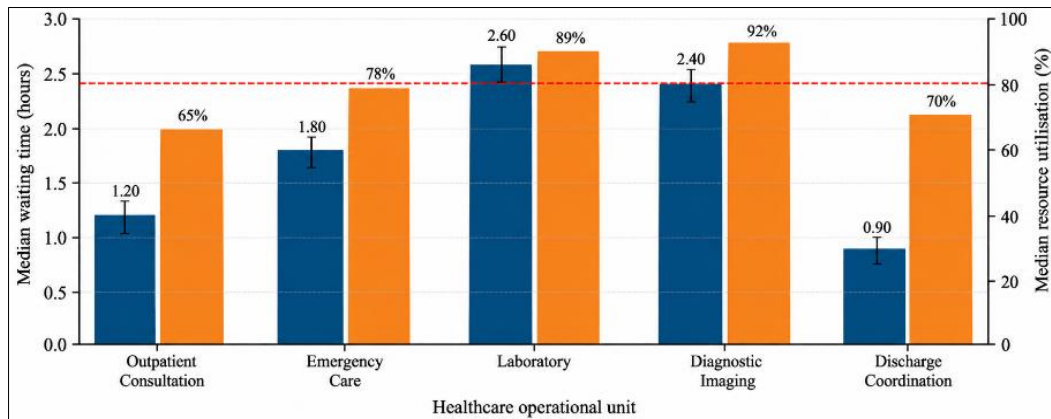


Fig. 3: Operational waiting time and resource utilization across healthcare units

The observed relationship should not be interpreted as a causal effect of utilization alone, as waiting was also associated with demand peaks, skill restrictions, interdepartmental handoffs, and repeated activities. Similar healthcare process-mining research reports that waiting time and resource workload can identify bottlenecks at service units and reveal interactions among overloaded departments

iii. Allocation performance

The proposed allocation model was compared with a simulated baseline roster. Demand coverage increased from 78.1% to 88.7%, while median waiting

time decreased from 1.70 to 1.29 hours and 90th-percentile waiting time from 4.60 to 3.42 hours. The workload coefficient of variation declined from 0.31 to 0.21, indicating more balanced workload distribution. Overtime exposure decreased from 12.4% to 8.9% of staffed shifts. No hard skill or availability constraints were violated. Human reviewers modified 8.7% of recommendations, mainly during demand surges, staff absence, and cases requiring information not captured in the event log. The largest improvements occurred in diagnostic imaging and emergency care, while the effect was smaller in outpatient consultation due to more stable appointment schedules and staffing.

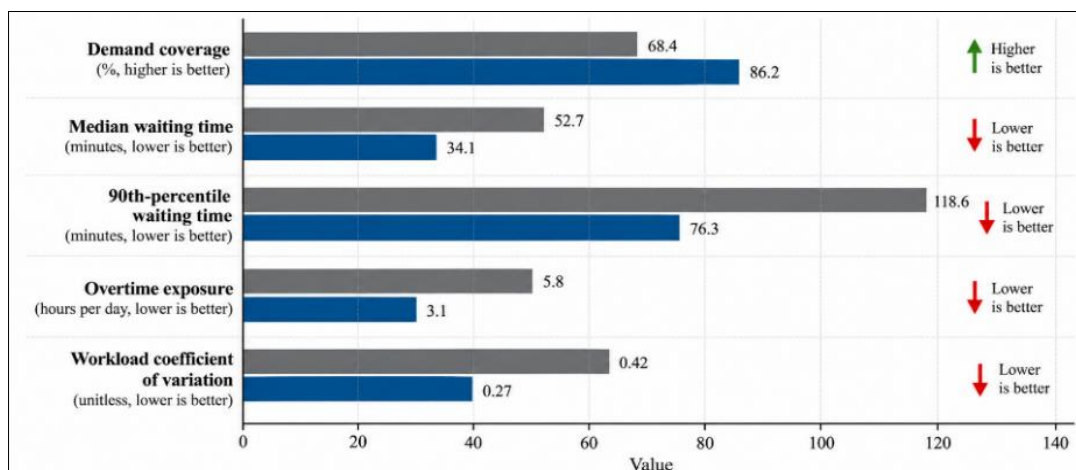


Fig. 4: Baseline and explainable allocation performance across operational indicators

Table III: Comparative Performance of the Historical Roster and Explainable Allocation Model

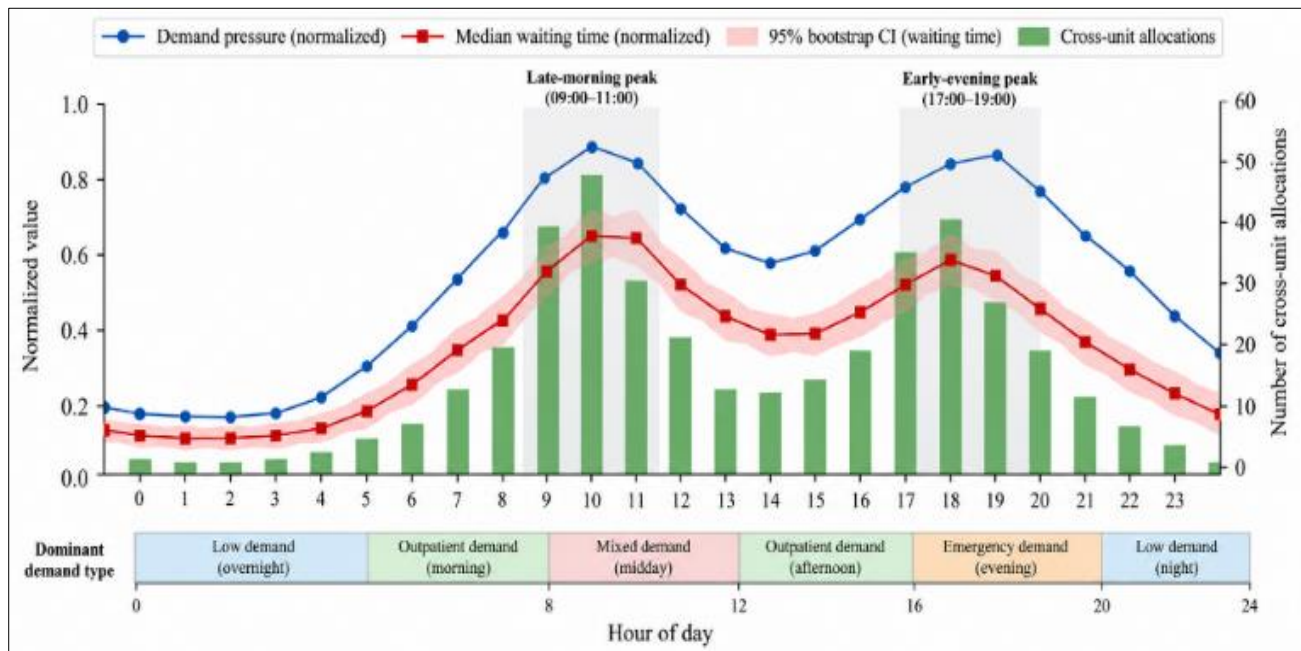
Performance indicator	Historical roster	Explainable allocation	Relative change
Demand coverage	78.1%	88.7%	+13.6%
Median waiting time	1.70 h	1.29 h	-24.1%
90th-percentile waiting time	4.60 h	3.42 h	-25.7%
Overtime exposure	12.4%	8.9%	-28.2%
Workload coefficient of variation	0.31	0.21	-32.3%
Feasible assignment rate	96.8%	100.0%	+3.2 percentage points
Conformance deviation rate	14.6%	9.8%	-32.9%
Supervisor override rate	Not recorded	8.7%	—
Mean allocation score	Not available	0.74	—

The table supplies the exact values behind the graph and separates service, workforce, feasibility, and governance outcomes. The historical roster did not contain a standardized override record; therefore, direct comparison of override rates was not possible.

iv. Temporal demand and workforce pressure

Demand pressure increased during two recurring periods: late morning, linked to outpatient

arrivals and diagnostic orders, and early evening, linked to emergency admissions and delayed diagnostic completion. The allocation model responded by assigning more eligible staff to diagnostic and emergency units. The largest waiting-time reduction occurred during the early evening peak, when demand most exceeded specialized staff availability. Gains were smaller during low-demand periods because baseline staffing was already sufficient.

**Fig. 5: Temporal relationship between demand pressure, waiting time, and allocation response**

The temporal pattern supports the view that workforce allocation should respond to process state rather than rely only on fixed daily staffing ratios. The result also indicates that allocation decisions need current demand information, current staff availability, and skill restrictions at the time of recommendation.

v. Explainability and governance results

Demand pressure was the most frequent positive contributor to allocation priority, followed by skill compatibility and availability, while existing workload was the main negative contributor. Governance risk acted as a hard exclusion criterion when qualification or availability rules were violated. Local

explanations were available for 100% of accepted and rejected recommendations and included the selected resource, score components, eligibility status, model version, and reviewer action. Overrides were more common during unexpected staff absence, equipment downtime, and urgent cases with missing event-log information. Key concerns included incomplete workload records, difficulty representing continuity of care across units, and unsuitable high scores when supervisors had contextual information not captured in the data. These findings support human review during operational deployment.

B. DISCUSSION

The findings show that workforce allocation depends on demand, workflow dependencies, staff qualifications, and resource availability, not staffing totals alone. Waiting was concentrated at diagnostic, handoff, and approval interfaces, highlighting time-specific resource contention. Reduced workload variation indicates more balanced assignments, but equal workloads are not always appropriate because qualifications, task complexity, and working-time limits differ. The smaller reduction in waiting time shows that staffing cannot resolve delays caused by documentation, approvals, information dependencies, or delayed results. Explainable recommendations should identify demand, eligibility, workload, risk, and process state, while human review remains necessary for conditions absent from event logs. Deployment requires auditable records of data, model versions, recommendations, reviewer actions, and overrides. Hard constraints should remain separate from soft preferences. Composite utility should be interpreted with individual indicators to avoid hiding trade-offs among waiting time, overtime, workload balance, and policy compliance.

C. Limitations and future work

The study has several limitations. Event logs may omit informal coordination, verbal instructions, temporary staff exchanges, and undocumented interruptions. Retrospective replay cannot fully represent behavioural responses during deployment, and allocation weights require local calibration. Differences in workflows, staffing, regulations, and digital systems limit transfer across healthcare settings. Fairness assessment may also be affected by qualifications, availability, shifts, and department-specific demand. Future research should conduct prospective multi-site validation and evaluate privacy-preserving cross-institutional data approaches. Digital-twin or discrete-event simulation could assess demand surges, staff absence, diagnostic failures, and emergency transfers. Further work should incorporate fatigue, patient acuity, task complexity, and uncertainty, while examining explanation comprehension, reviewer trust, override behaviour, and perceived autonomy.

V. CONCLUSION

This study developed an explainable process-intelligence framework for workforce allocation and operational governance in digital healthcare systems. The framework integrates event-log preparation, process discovery, bottleneck analysis, resource eligibility, explainable allocation scoring, and audit-based governance. Diagnostic imaging, laboratory validation, and cross-unit handoffs generated the greatest waiting burden. The model increased demand coverage from 78.1% to 88.7%, reduced the workload coefficient of variation from 0.31 to 0.21, lowered median waiting time from 1.70 to 1.29 hours, and reduced overtime exposure from 12.4% to 8.9%. Policy deviations also decreased, while explanations supported review and reconstruction

of allocation decisions. The framework supports supervisors, workforce planners, operations managers, and healthcare governance teams in shift planning, diagnostic-capacity management, handoff monitoring, workload review, and audit preparation. Its value lies in showing both staff assignments and the operational conditions and constraints behind each recommendation. Future work should use prospective multi-site studies with richer staff-availability, patient-acuity, fatigue, and staff-feedback data, while testing alternative weighting schemes, long-term fairness, rare demand conditions, and human overrides.

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