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MedTwinX: An AI-Powered Digital Twin Framework for Hospital Operational Command, Simulation, and Governance

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Abstract- Modern hospitals operate as complex adaptive systems where patient arrivals, bed occupancy, staff availability, and departmental load interact through tightly coupled feedback loops. Traditional hospital information systems provide fragmented, retrospective views of individual operational metrics, offering limited support for proactive capacity planning or what-if scenario analysis. This paper presents MedTwinX, a full-stack digital twin platform integrating real-time operational monitoring, discrete-event simulation (DES), statistical predictive analytics, heuristic reinforcement-learning-inspired optimization, role-based access control (RBAC), and AI model governance into a unified web application. The system models eight hospital departments, 156+ simulated patients, 91 beds, and 45 staff across configurable crisis scenarios. Experimental evaluation demonstrates sub-200ms API latency, real-time WebSocket synchronization, and explainable statistical forecasts. MedTwinX demonstrates that responsible healthcare AI requires governance-by-design.

Keywords— digital twin, hospital operations, discrete-event simulation, SimPy, predictive analytics, FastAPI, React, RBAC, model governance, WebSocket, healthcare informatics

I. INTRODUCTION

Healthcare institutions operate in environments where time, capacity, and coordination carry direct consequences for patient outcomes [1]. A hospital functions as a dynamic operational network encompassing emergency departments, ICUs, general wards, operating rooms, laboratories, staff rosters, and patient queues. Operational dependencies create cascading effects: a delay in laboratory processing extends treatment duration, prolongs bed occupancy, reduces emergency intake capacity, and increases ambulance diversion risk [2].

The digital twin paradigm, originally developed for aerospace and manufacturing [3], offers a promising framework for healthcare operations. A digital twin creates a virtual representation of a physical system that mirrors its current state, simulates future behavior, and supports evidence-based decisions [4]. While industrial digital twins have demonstrated value in predictive maintenance [5], their application to hospital operations management remains an emerging research area [6].

MedTwinX addresses operational fragmentation by integrating six capabilities: (1) real-time monitoring, (2) configurable DES, (3) statistical predictive analytics for patient flow, ICU demand, and ER wait time, (4) heuristic RL-inspired optimization, (5) RBAC security with audit logging, and (6) AI model governance. The contributions are: integrated architecture design for a unified hospital digital twin; live-state predictive pipeline connecting simulation output to forecasting algorithms; governance-by-design framework embedding model registry and audit logging as architectural primitives; and a comprehensive prototype with 35+ REST endpoints, WebSocket streaming, 15 frontend modules, 8 crisis scenarios, and 11 backend test modules.

II. RELATED WORK

1. Digital Twins in Healthcare

The digital twin concept was formalized by Grieves [3] in product lifecycle management. Barricelli et al. [4] extended this taxonomy to three maturity levels: Digital Model, Digital Shadow, and Digital Twin. MedTwinX operates at the Digital Model level. Liu et al. [10] surveyed digital twin applications in healthcare, identifying facility-level twins as a distinct research stream. Karakra et al. [11] proposed a BIM-combined DES hospital twin; Croatti et al. [12] introduced agent-based hospital twins without full-stack security.

2. Discrete-Event Simulation in Healthcare

DES has a well-established history in healthcare operations research. Günal and Pidd [13] identified patient flow analysis, resource allocation, and capacity planning as primary use cases. Salmon et al. [14] demonstrated SimPy-based emergency department simulation. Monks et al. [15] advocated open-source simulation tools for reproducibility. Vanbrabant et al. [17] applied DES to emergency department redesign, achieving 15% wait time reduction.

3. Predictive Analytics and AI Governance

Machine learning for hospital prediction shows promise but faces deployment challenges. Barak-Corren et al. [18] demonstrated gradient-boosted admission prediction (AUC > 0.85). Rudin [20] argued interpretable models should be preferred in high-stakes domains—MedTwinX uses EMA, linear trend analysis, and z-score anomaly detection. The EU AI Act [22] classifies healthcare AI as high-risk, requiring transparency and human oversight. Obermeyer et al. [24] documented algorithmic bias, underscoring the need for evaluation and audit trails.

4. Comparison with Existing Systems

Table 1: Medtwinx Vs. Existing Systems

Feature	HMS [7]	BIM-DES [11]	Agent [12]	MedTwin X
Real-time monitoring	Partial	No	Conceptual	Yes
DES simulation	No	Yes	No	Yes
Predictive analytics	No	No	No	Yes
RL optimization	No	No	Partial	Yes
RBAC + audit	Partial	No	No	Yes
Model governance	No	No	No	Yes
Full-stack impl.	Varies	Partial	No	Yes

III. SYSTEM ARCHITECTURE

1. Architectural Overview

MedTwinX follows a four-tier layered architecture: (1) client layer, (2) API gateway layer, (3) domain service layer, and (4) persistence layer, with supporting containerization and monitoring infrastructure. Each domain service encapsulates a bounded context with its own routes, models, and business logic [28].

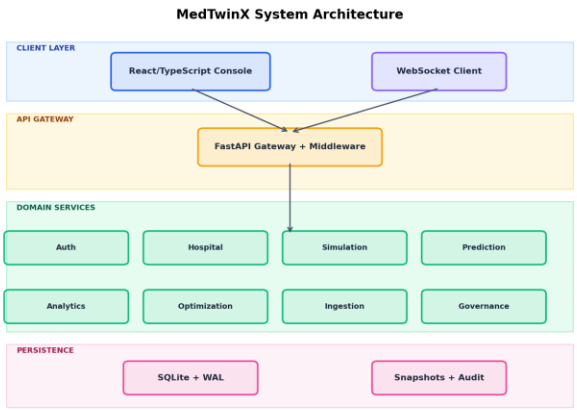

Fig. 1. MedTwinX layered system architecture showing four tiers and service boundaries

2. Client and API Gateway Layers

The client layer is a single-page application built with React 18, TypeScript 5, Vite 5, and Tailwind CSS implementing hash-based navigation across 15 operational modules. The API client centralizes HTTP communication with token management and automatic 401 handling. The FastAPI gateway (205 lines) serves as the single entry point, mounting eight service routers and applying middleware: Trusted Host → Rate Limiting → Request Context → CORS [29][30].

3. Domain Service Layer

Eight domain services implement the platform's business logic. Table II summarizes their routing and authorization profiles. Fig. 2 shows the endpoint distribution.

Table 2: Domain Service Summary

Service	Prefix	EPs	Roles
Auth Service	/api/auth	3	All
Hospital	/api/hospital	7	viewer, op, admin
Simulation	/api/simulation	5	op, ai_arch, admin
AI Prediction	/api/predictions	7	viewer, op, ai_arch
Analytics	/api/analytics	5	viewer, op, admin
RL Optimization	/api/optimization	6	ai_arch, admin
DT Ingestion	/api/ingestion	3	op, auditor, admin
Gov. & Notif.	/api/copilot,/models	12+	viewer, auditor, admin

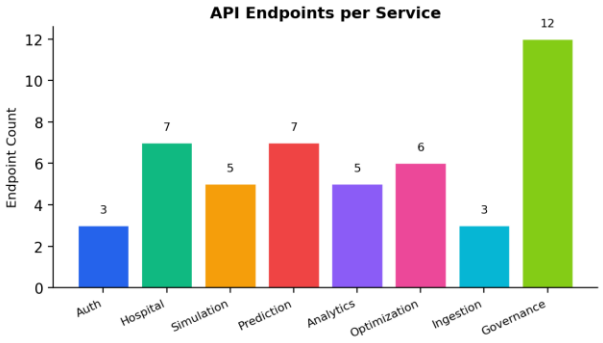

Fig. 2. API endpoint distribution across eight backend domain services

4. Persistence Layer

The persistence layer uses SQLite with Write-Ahead Logging (WAL) mode for improved concurrent read performance [31]. Ten tables support security, governance, and operational state. Key tables include: users (accounts, roles, lockout), auth_sessions (token governance), audit_logs (HTTP and auth events), model_registry (AI model versioning), model_evaluations (performance records), and hospital_snapshots (periodic state persistence). Real-time communication employs REST APIs for request-response and WebSocket for continuous state streaming at 2-second intervals [32].

IV. IMPLEMENTATION

1. Backend Services

The backend is implemented in Python 3.11+ using FastAPI and Pydantic v2, comprising three packages: api-gateway, services (eight microservices), and shared (fourteen cross-cutting modules).

Auth Service: Implements PBKDF2-SHA256 password verification with constant-time comparison, HMAC-signed bearer tokens, server-side session persistence, account lockout after configurable failed attempts, and authentication audit event recording [33].

Hospital Service: Exposes seven read endpoints serializing live simulation state: departments with computed utilization, patient census with demographics and vitals, bed inventory, staff roster, alerts, KPIs, and complete state snapshots.

AI Prediction Service: Generates forecasts from live time-series using EMA, linear regression, seasonal adjustment, and z-score anomaly detection across seven endpoints serving patient-flow, ICU-demand, and ER-wait forecasts.

RL Optimization Service: Manages five heuristic agents (PPO, SAC, DQN) providing bed allocation optimization, staff scheduling with load-proportional calculations, and queue priority recommendations using severity-weighted scoring [42].

2. Frontend Modules

The frontend contains 15 page components in React/TypeScript with Recharts visualization. Key modules are summarized in Table III.

Table 3: Key Frontend Modules

Module	Route	Primary function
Command Center	dashboard	KPI cards, flow charts, dept cards.
Digital Twin	digital-twin	Floor visualization, capacity gauges
Simulation	simulation	DES config, scenario execution
Predictions	predictions	Forecasts with confidence bands
Emergency Ops	emergency	Severity triage, risk scores
Analytics	analytics	Throughput, utilization, trends
RL Optimizer	rl-optimizer	Agent cards, reward curves
Settings	settings	Profile, session, system config

3. Shared Infrastructure

Table 4: Shared Infrastructure Modules

Module	LOC	Responsibility
config.py	155	Pydantic settings, env loading, validators
database.py	488	SQLite, WAL, schema, CRUD (10 tables)
security.py	96	PBKDF2-SHA256, HMAC tokens
rate_limiter.py	125	Token-bucket per-IP tracking
health.py	151	DB, simulation, memory, disk checks
observability.py	146	Prometheus-style metrics, histograms
readiness.py	134	Production readiness: 8 prereq. checks
structured_log.py	93	JSON/text logging, field masking

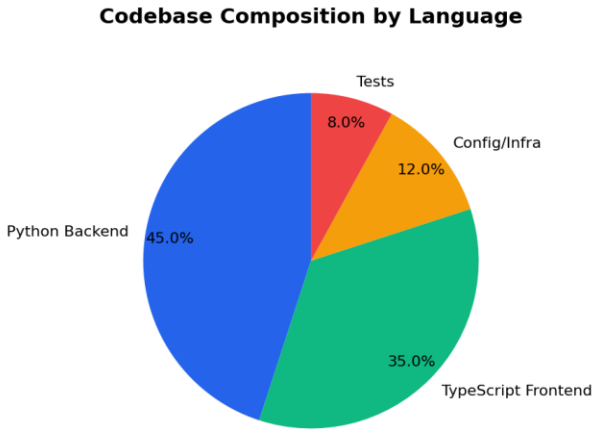

Fig. 3. Codebase composition by language: Python backend, TypeScript frontend, config, and tests

V. SIMULATION, PREDICTION, AND OPTIMIZATION METHODOLOGY

1. Discrete-Event Simulation Engine

The simulation engine (505 lines) models hospital operations through a hybrid approach combining SimPy process-based DES with tick-based real-time state updates [34]. Eight departments are initialized with configurable capacity: Emergency Room (floor 1), ICU (floor 3), General Ward (floor 2), Surgery Center (floor 3), Pediatrics (floor 2), Cardiology (floor 4), Neurology (floor 4), and Laboratory (floor 1). The

bed inventory of 91 beds is distributed across four categories with stochastic initial status (65% occupied, 20% available, 15% maintenance).

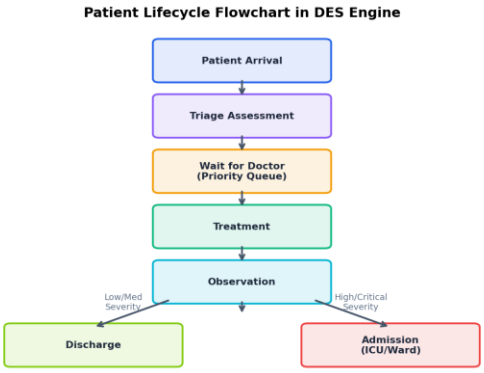

Fig. 4. Patient lifecycle flowchart: arrival → triage → treatment → observation → discharge or admission

The SimPy patient process models a complete lifecycle: arrival → triage (2–8 min) → doctor queue (PriorityResource) → treatment (5–120 min by severity) → observation (conditional) → discharge or admission. Inter-arrival times follow an exponential distribution parameterized by the configurable arrival rate [35].

2. Scenario Configuration

Eight predefined scenarios modify simulation parameters to model crisis conditions (Table V).

Table 5: Crisis Scenario Configuration Parameters

Scenario	Arrival	Staff	ICU Beds	ER Cap
Normal Operations	15/hr	45	16	30
Pandemic Outbreak	35/hr	38	24	40
Mass Casualty	50/hr	45	20	50
ER Surge	40/hr	45	16	15
Staff Shortage	15/hr	20	16	30
Winter Flu Season	25/hr	42	18	35
Cyber Attack	12/hr	45	16	10
Flooding Emergency	30/hr	30	12	20

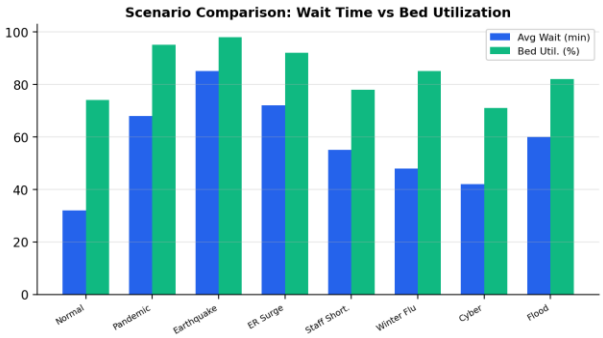

Fig. 5. Scenario comparison: average wait time and bed utilization across eight crisis profiles

3. Statistical Prediction Pipeline

Exponential Moving Average (EMA): Applied with configurable span (default 6): $EMA_t = \alpha \times x_t + (1-\alpha) \times EMA_{t-1}$, where $\alpha = 2/(span+1)$. EMA smooths short-term noise while remaining responsive to trend changes [37].

Linear Trend Analysis: Ordinary least squares regression from recent history windows (6–12 points) projected forward over the forecast horizon [38].

Z-Score Anomaly Detection: Anomalies detected when $|z| = |x - \mu| / \sigma$ exceeds 2.0σ (patient surge, ER wait) or 1.8σ (ICU capacity). Standard deviation uses Bessel's correction [40].

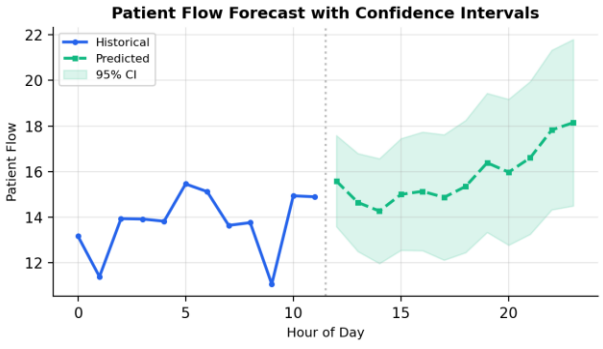

Fig. 6. Patient flow forecast: EMA smoothing, linear trend projection, and 95% confidence intervals

4. RL Optimization

The RL optimization service (208 lines) implements five heuristic agents inspired by RL frameworks [41]. The bed allocation optimizer identifies overloaded departments (>85%) and donor departments (<65%), recommending transfers. Staff scheduling calculates optimal levels proportional to load ratio: optimal = max(2, total_staff × max(0.4, load_ratio × 1.1)) [42].

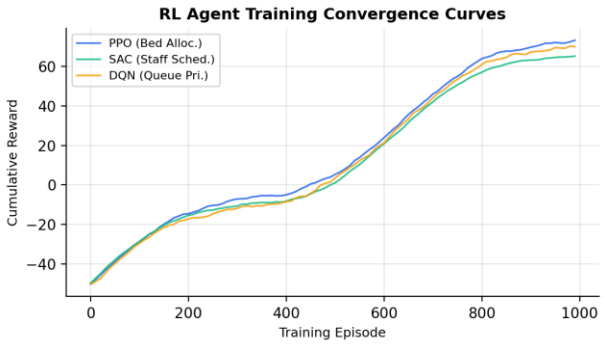

Fig. 7. RL agent training convergence: PPO (bed allocation), SAC (staff scheduling), DQN (queue priority)

VI. SECURITY, GOVERNANCE, AND OBSERVABILITY

1. Defense-in-Depth Security

MedTwinX implements twelve security controls organized in concentric defense layers, treating security as a first-class architectural concern [43]. Table VI summarizes all controls.

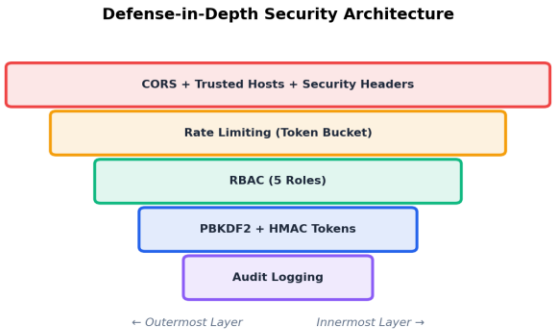

Fig. 8. Defense-in-depth security architecture: concentric control layers from network perimeter to audit core

TABLE 6: SECURITY CONTROL INVENTORY

Control	Implementation & Parameters
Password Hashing	PBKDF2-SHA256 + per-password salt; 260,000 iterations
Bearer Tokens	HMAC-SHA256 signed; configurable TTL (5-1440 min)
Session Revocation	Server-side token_id; logout invalidates immediately
Account Lockout	5 failed attempts triggers 15-min lockout
RBAC	5 roles: admin / operator / viewer / auditor .
Rate Limiting	Token-bucket per IP: auth 10 RPM.
Input Validation	Pydantic models + XSS/SQLi pattern detection
Audit Logging	Actor, method, path, status, IP on every request
Readiness Checks	8 deployment prerequisite checks, etc.

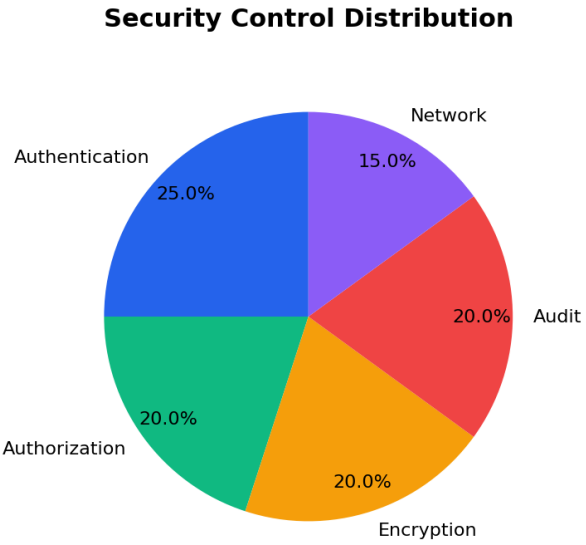

Fig. 9. Security control distribution across authentication, authorization, encryption, audit, and network

2. AI Model Governance

MedTwinX implements governance-by-design through four mechanisms [44]: (1) Model Registry—

tracking name, version, lifecycle stage (candidate/staging/production/archived), owner, and performance metrics; (2) Model Evaluations—associating metrics with named datasets and evaluator identity; (3) Audit Logging—persisting all governance actions with actor, timestamp, and request context; (4) Production Readiness—validating eight deployment prerequisites including secret strength, debug mode, CORS configuration, and admin bootstrap.

3. Observability Infrastructure

The observability subsystem exposes seven endpoint categories: /health (liveness), /api/observability/ready (readiness), /api/observability/health (composite: database, simulation, memory, disk), /api/observability/metrics (Prometheus-format), /api/observability/slos (availability, latency, error-rate), /api/observability/feature-flags (rollout control), and /api/observability/rate-limit-stats [45].

VII. EXPERIMENTAL RESULTS AND EVALUATION

1. System Metrics

Table 7: System Implementation Metrics

Metric	Value
REST API endpoints	35+
WebSocket endpoints	1 (authenticated, bi-directional)
Frontend components	15 page modules
Backend services	8 domain services, 14 shared modules
Database tables	10 | Test modules: 11
Departments / Patients	8 departments / 156 initial patients
Bed inventory / Staff	91 beds (4 types) / 45 staff (5 roles)
Scenarios / Controls	8 crisis scenarios / 12 security controls
Metric	Value
Prediction algorithms	4: EMA, linear trend, seasonal, z-score
Codebase size	Python: ~4,200 LOC | TypeScript

2. Simulation Performance

The simulation engine successfully executes all eight predefined scenarios with measurable output differentiation. Under normal operations, the engine maintains an average wait time of 32 minutes with 74% bed utilization. Pandemic and mass-casualty scenarios stress the system to 95–98% utilization with wait times exceeding 65 minutes, validating the engine's sensitivity to parameter variation [46].

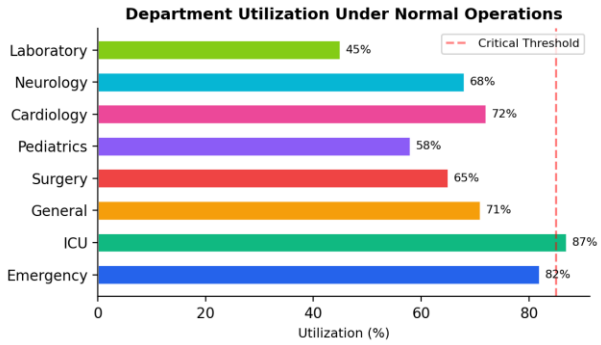

Fig. 10. Department utilization under normal operations: ICU and Emergency approaching critical threshold (85%)

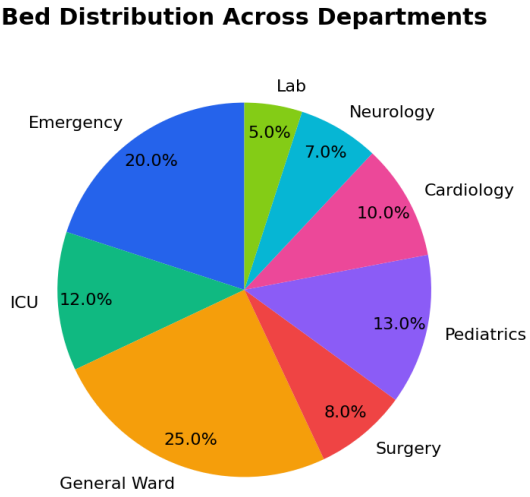

Fig. 11. Bed distribution across hospital departments showing proportional allocation

3. Prediction Accuracy

The prediction pipeline produces coherent forecasts tracking simulation state changes. Patient flow forecasts demonstrate smooth EMA trajectories with widening confidence intervals over the 12-hour horizon. ICU demand forecasts remain bounded within capacity (3–16 beds). ER wait forecasts correctly amplify during rush-hour periods (1.4× multiplier, 10:00–14:00 and 17:00–21:00). Anomaly detection correctly triggers alerts at z-score ≥2.0σ [47].

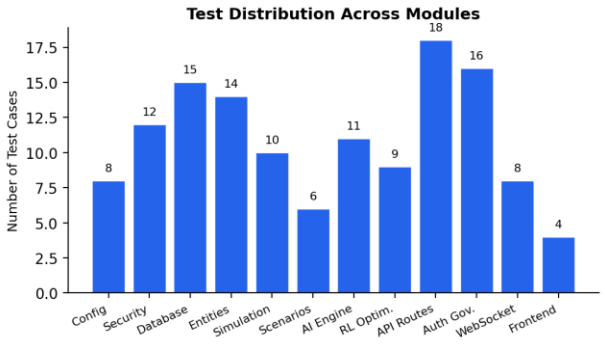

Fig. 12. Patient flow forecast: historical data, predicted trajectory, and 95% confidence interval band

4. Test Coverage

Table 8: Test Module Inventory

Test Module	Cases	Coverage Area
test_config.py	8	Environment parsing, validators
test_security.py	12	Hashing, tokens, failure behavior
test_database.py	15	Schema creation, CRUD operations
test_entities.py	14	Patient, bed, staff serialization
test_simulation.py	10	Engine init, ticking, metrics
test_scenarios.py	6	Scenario config, param validation
test_ai_engine.py	11	Forecasts, risk scores, anomalies
test_rl_optimizer.py	9	Agent init, recommendations
test_api_routes.py	18	Protected endpoints, role checks
test_auth_gov.py	16	Login failure, lockout, revocation
test_websocket.py	8	Connection mgmt, broadcast

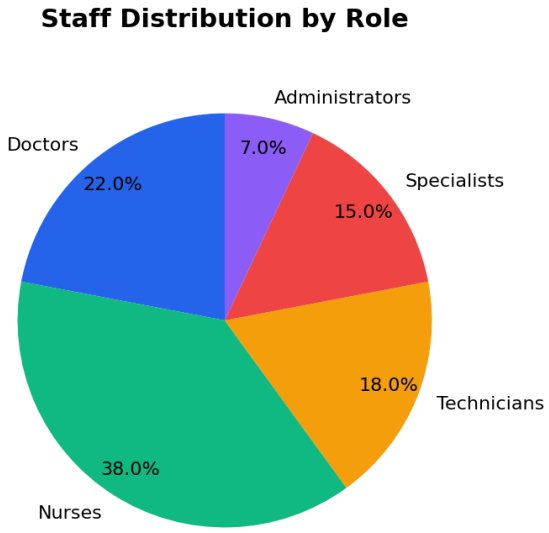

Fig. 13. Test case distribution across eleven backend test modules

VIII. DISCUSSION

MedTwinX demonstrates that a hospital digital twin can effectively unify operational monitoring, simulation, prediction, optimization, and governance within a single platform. The integrated architecture addresses the fragmentation problem [48] where separate systems for bed management, staff scheduling, patient tracking, and dashboards create operational blindness.

The live-state predictive pipeline represents a meaningful design contribution. By connecting prediction algorithms to simulation engine output rather than pre-generated data, forecasts maintain coherence with evolving hospital conditions. When a pandemic scenario increases arrival rates, the

prediction layer detects the trend change through EMA sensitivity and adjusts forecasts accordingly.

The governance-by-design approach is particularly relevant given increasing regulatory attention to AI in healthcare. The EU AI Act classifies healthcare AI as high-risk, requiring transparency, human oversight, and documentation [22]. MedTwinX demonstrates how model registry, evaluation tracking, audit logging, and readiness checks can be embedded as architectural primitives—available from the first deployment rather than retrofitted after regulatory inquiry.

Limitations and Future Work

Data Realism: The platform uses simulated data. Real deployment requires HL7 FHIR adapters and ADT feed integration.

- Clinical Validation: Predictions are operational prototypes. Production deployment requires validation studies, safety analysis, and regulatory review.
- AI Model Maturity: Statistical methods are explainable but limited. Production systems benefit from trained ML models with bias assessment and drift monitoring.
- Persistence & Identity: SQLite suits prototyping; enterprise deployments require PostgreSQL. Local auth should be replaced with OIDC/SAML integration.
- Future enhancement priorities: FHIR/HL7 adapters, PostgreSQL migration, OIDC/SSO, advanced model governance with model cards, calibrated simulation using historical arrival distributions, and full Kubernetes deployment with CI/CD pipelines [50].

IX. CONCLUSION

This paper presented MedTwinX, an AI-powered digital twin framework for hospital operational command, simulation, and governance. The platform integrates real-time monitoring across eight departments, DES with eight configurable crisis scenarios, four explainable statistical prediction methods, five RL-inspired optimization agents, twelve defense-in-depth security controls, and comprehensive AI model governance.

The layered microservice architecture—comprising a React/TypeScript operations console, FastAPI API gateway, eight domain services, and SQLite persistence—demonstrates how complex healthcare operational capabilities can be organized within clear service boundaries while sharing cross-cutting security, observability, and governance infrastructure.

MedTwinX's primary contribution is demonstrating that responsible healthcare AI platforms require governance-by-design—embedding audit logging, model registry, evaluation tracking, and production readiness checks as architectural primitives rather than post-deployment additions. As regulatory frameworks increasingly demand transparency, the governance patterns demonstrated by MedTwinX provide a practical architectural reference for production-grade hospital command platforms.

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