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A Real-Time Hospital Capacity Intelligence Framework for Operational Resilience

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Abstract

In an era of escalating healthcare demands, hospitals face persistent challenges in maintaining operational resilience amid fluctuating patient volumes, resource constraints, and unforeseen disruptions. This conceptual manuscript introduces a novel framework for real-time hospital capacity intelligence, designed to enhance decision-making through integrated AI-driven analytics and interoperable data ecosystems. Drawing on theoretical foundations from clinical AI architectures, healthcare analytics infrastructures, and decision support pipelines, the proposed system emphasizes seamless integration with electronic health records (EHRs), governance mechanisms for AI deployment, and dynamic monitoring to mitigate risks such as capacity overloads. The framework outlines a layered architecture that orchestrates data exchange, predictive analytics, and adaptive resource allocation, ensuring interoperability across clinical workflows. Key conceptual formulas are presented to interpret risk propagation in capacity management, decision confidence in real-time intelligence, and governance load in system operations. By synthesizing recent peer-reviewed literature on AI governance and clinical interoperability, this work highlights the potential for such frameworks to foster resilient hospital operations without relying on empirical data or model evaluations. Implications for healthcare systems include improved preparedness for surges, ethical AI integration, and scalable intelligence ecosystems. This theoretical exploration underscores the need for robust, AI-augmented infrastructures to support sustainable healthcare delivery.

Keywords Clinical decision support, EHR interoperability, Hospital capacity intelligence, Operational resilience, Real-time AI frameworks, AI governance in healthcare

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Introduction

The landscape of modern healthcare is characterized by dynamic pressures that test the limits of hospital operational resilience. From pandemics to seasonal influxes, hospitals must navigate capacity constraints while ensuring patient safety and resource efficiency [1, 2]. This manuscript proposes a conceptual framework for real-time hospital capacity intelligence, aiming to theoretically bolster resilience through AI-integrated systems that prioritize predictive foresight and adaptive governance. Unlike empirical studies, this work focuses on architectural designs and theoretical analytics, synthesizing insights from clinical AI system architectures and healthcare analytics infrastructures to envision a resilient ecosystem.

Clinical settings demanding capacity intelligence integration

In acute care environments, such as emergency departments and intensive care units, real-time capacity intelligence becomes pivotal for operational resilience. These settings often experience volatile patient flows, where delays in bed allocation or staffing can cascade into systemic inefficiencies [3, 4]. Theoretical models from EHR intelligence ecosystems suggest that embedding AI-driven monitoring could preemptively identify bottlenecks, drawing on decision support pipelines to simulate workflow optimizations without actual data trials [5]. By anchoring intelligence frameworks to clinical settings, hospitals can conceptually align AI architectures with frontline needs, fostering interoperability that transcends siloed data sources [6].

Data modalities shaping hospital resilience frameworks

Hospital capacity intelligence relies on diverse data modalities, including structured EHR entries, sensor-derived metrics from bed occupancy systems, and unstructured notes from clinical workflows [7, 8]. Theoretical explorations in healthcare analytics infrastructures emphasize the role of multimodal data fusion in enhancing resilience, where AI governance ensures ethical handling and monitoring of these inputs [9]. For instance, interoperability frameworks could theoretically harmonize real-time feeds from wearable devices and administrative databases, enabling a cohesive intelligence layer that anticipates capacity strains [10]. This modality-focused approach underscores the need for robust data exchange protocols to support operational decision-making in resilient systems [11].

Deployment environments for real-time intelligence orchestration

Deploying hospital capacity intelligence frameworks in hybrid environments—spanning on-premise servers and cloud-based analytics—presents unique theoretical challenges for resilience [12, 13]. AI deployment systems must account for latency in real-time processing, where governance and monitoring mitigate risks like data drift or integration failures [14]. Conceptual architectures advocate for containerized modules that facilitate seamless updates, ensuring that decision support pipelines remain agile amid evolving hospital demands [15]. In such environments, theoretical interoperability standards could enable cross-institutional capacity sharing, enhancing overall healthcare ecosystem resilience [16].

Governance constraints in capacity intelligence ecosystems

Governance emerges as a core constraint in designing real-time hospital capacity intelligence for operational resilience, encompassing ethical AI use, bias mitigation, and regulatory compliance [17, 18]. Literature on AI governance in healthcare highlights the necessity of monitoring frameworks that theoretically audit decision support outputs, preventing unintended escalations in capacity mismanagement [19]. By integrating governance into the architectural core, systems can conceptually balance innovation with accountability, ensuring that intelligence pipelines align with clinical ethics and data privacy standards [20]. This constraint-driven perspective is essential for sustainable deployment in resilience-focused hospital settings [21].

Workflow integration models enhancing resilience dynamics

Clinical workflow integration models form the backbone of effective hospital capacity intelligence, theoretically linking AI analytics to daily operations for resilience [22, 23]. These models propose modular interfaces that embed intelligence into EHR ecosystems, allowing real-time adjustments to staffing and resource allocation without disrupting care delivery [24]. Decision support pipelines, when theoretically orchestrated, could amplify workflow efficiency by providing contextual alerts on capacity thresholds [25]. Anchoring integration to resilience dynamics ensures that frameworks adapt to emergent scenarios, such as surge events, through governed AI interactions [26].

This introduction sets the stage for a deeper theoretical synthesis, positioning the proposed framework as a conceptual advancement in AI-augmented hospital operations. By addressing these facets, the manuscript contributes to the discourse on resilient healthcare systems, highlighting systemic pressures that necessitate intelligence-driven resilience infrastructures **(Table 1).**

Table 1. Operational stressors driving demand for real-time capacity intelligence in hospitals

Operational stressor	Hospital impact domain	Resilience risk introduced	Intelligence mitigation role
Pandemic surges	ICU and ED saturation	Bed shortages	Predictive surge forecasting
Seasonal epidemics	Admission volatility	Staffing strain	Workforce optimization alerts
Emergency clustering events	Trauma units	Resource bottlenecks	Real-time triage redistribution
Elective procedure backlogs	Surgical wards	Throughput delays	Scheduling recalibration
Staffing absenteeism	Nursing operations	Care continuity risks	Dynamic staffing models
Supply chain disruptions	Equipment availability	Treatment delays	Inventory intelligence tracking

Theoretical Background and Literature Synthesis

The theoretical underpinnings of real-time hospital capacity intelligence frameworks draw from advancements in clinical AI system architectures and healthcare analytics infrastructures, emphasizing conceptual designs that enhance operational resilience. This section synthesizes peer-reviewed literature from 2017 to 2024, focusing on EHR intelligence ecosystems, decision support pipelines, AI governance, interoperability frameworks, and clinical workflow integration models. By integrating these domains, we establish a foundation for the proposed architecture, highlighting theoretical synergies and gaps.

Evolving paradigms in clinical AI architectures for capacity management

Clinical AI architectures have progressed toward modular, scalable designs that theoretically support real-time capacity intelligence in hospitals [8, 27]. Recent conceptual works advocate for layered systems where AI components process EHR data to forecast bed availability and patient throughput, without empirical validation [7]. For instance, architectures incorporating generative AI elements could theoretically simulate capacity scenarios, aligning with governance needs to ensure ethical deployment [1]. These paradigms underscore the shift from static models to dynamic ones, where intelligence orchestration mitigates operational disruptions [14]. Literature emphasizes the role of AI in augmenting human decision-making, proposing theoretical pipelines that integrate predictive analytics into resilience strategies [9].

Healthcare analytics infrastructures supporting resilience

Healthcare analytics infrastructures provide the theoretical backbone for hospital capacity intelligence, focusing on data aggregation and processing frameworks [12, 28]. Conceptual models highlight the importance of cloud-native infrastructures that enable real-time analytics, theoretically reducing latency in capacity assessments [13]. Synthesis of studies reveals a consensus on the need for robust data lakes that harmonize disparate sources, such as administrative and clinical datasets, to foster resilience [6]. AI-driven infrastructures are theorized to incorporate monitoring mechanisms that detect anomalies in capacity utilization, drawing on governance protocols to maintain system integrity [5, 19]. This infrastructural lens reveals opportunities for intelligence frameworks to optimize resource flows in high-stakes environments [22] theoretically.

EHR intelligence ecosystems and data exchange

EHR intelligence ecosystems are central to theoretical frameworks for operational resilience, enabling seamless data exchange across hospital systems [11, 16]. Literature synthesizes interoperability standards like FHIR, which conceptually facilitate real-time capacity intelligence by linking EHRs to AI analytics [10]. Theoretical explorations propose ecosystem designs that incorporate federated learning principles, allowing decentralized intelligence without compromising data sovereignty [15]. Governance in these ecosystems is critical, with conceptual checklists addressing ethical considerations in AI-EHR integrations [1, 20]. By synthesizing these insights, we identify a gap in frameworks that fully orchestrate EHR-derived intelligence for capacity resilience, particularly in multi-site hospital networks [6, 21].

Decision support pipelines in clinical contexts

Decision support pipelines represent a key theoretical pillar, conceptualizing AI as an enhancer of clinical judgments in capacity-constrained settings [18, 23]. Recent syntheses describe pipelines that theoretically process real-time inputs to generate capacity alerts, integrated with workflow models for seamless adoption [17, 24]. AI governance ensures these pipelines remain transparent, with monitoring systems theoretically auditing outputs to prevent bias amplification [4, 19]. Literature highlights the potential for ontology-based pipelines in nutrition or oncology analogs, adaptable to capacity intelligence [20, 25]. This synthesis points to the need for pipelines that incorporate feedback loops, theoretically improving resilience through iterative refinements [14, 27].

AI governance, monitoring, and deployment systems

AI governance and monitoring systems are theoretically indispensable for deploying hospital capacity intelligence frameworks [5, 26]. Conceptual guidelines advocate for continual monitoring to address drift in real-time analytics, ensuring alignment with clinical ethics [7, 15]. Synthesis reveals frameworks like DECIDE-AI, which provide reporting standards for early-stage AI evaluations, adaptable to capacity contexts [14]. Deployment systems emphasize self-governance models, theoretically fostering trust in AI-augmented resilience [28]. Monitoring burdens are conceptualized through formulas that interpret governance loads, highlighting the balance between oversight and operational efficiency [3, 9].

Interoperability and workflow integration models

Interoperability frameworks and clinical workflow integration models round out the theoretical synthesis, enabling cohesive capacity intelligence [13, 22]. Conceptual architectures propose standardized data exchange to support real-time resilience, with integration models theorizing AI embeddings in daily workflows [16, 23]. Literature synthesizes challenges in wide-scale AI deployment, advocating for strategies that enhance interoperability in governance-constrained environments [26, 27]. By addressing these, frameworks can theoretically transform hospital operations, filling gaps in resilience-focused intelligence systems [2, 8], and collectively forming the infrastructural substrate for resilience-oriented intelligence ecosystems **(Table 2)**.

Table 2. AI and data infrastructure domains supporting hospital capacity intelligence

Infrastructure domain	Theoretical function	Data sources integrated	Resilience contribution
Clinical AI architectures	Predictive capacity modeling	EHR and admissions data	Surge anticipation
Analytics infrastructures	Real-time processing	Administrative + clinical datasets	Throughput optimization
Interoperability frameworks	Cross-system exchange	FHIR, HL7 streams	Data liquidity
Decision support pipelines	Operational alerts	Bed + staffing metrics	Workflow acceleration
Governance systems	Ethical oversight	AI outputs, audit logs	Risk containment
Monitoring infrastructures	Drift detection	Temporal utilization trends	Intelligence stability

This synthesis illuminates the theoretical landscape, paving the way for an original architecture that advances real-time hospital capacity intelligence.

Orchestrating real-time hospital capacity intelligence infrastructure

The core of this conceptual manuscript is the orchestration of a real-time hospital capacity intelligence infrastructure, embodied in the adaptive capacity resilience orchestration network (ACRON). ACRON represents a unique layered architecture designed to theoretically enhance operational resilience through integrated AI governance, data interoperability, and dynamic decision support. Unlike prior frameworks, ACRON features a pentagonal layer structure—comprising ingestion, analytics, governance, orchestration, and feedback layers—interconnected via a helical feedback topology that spirals iterative refinements across layers, ensuring adaptive responses to capacity fluctuations.

The ingestion layer theoretically aggregates multimodal data from EHR ecosystems and sensor networks, facilitating real-time interoperability without empirical processing [6, 12]. The analytics layer employs conceptual AI pipelines to derive intelligence on capacity metrics, such as bed occupancy and staffing ratios [7, 18]. Governance layer embeds monitoring mechanisms to theoretically mitigate risks, incorporating ethical checklists for AI deployment [1, 5]. Orchestration layer coordinates decision support, theoretically allocating resources via predictive heuristics [14, 23]. The feedback layer introduces the helical topology, where outputs loop back nonlinearly, amplifying resilience through cumulative learning cycles, embedding ethical monitoring within intelligence flows across operational strata **(Figure 1)** [15, 19].

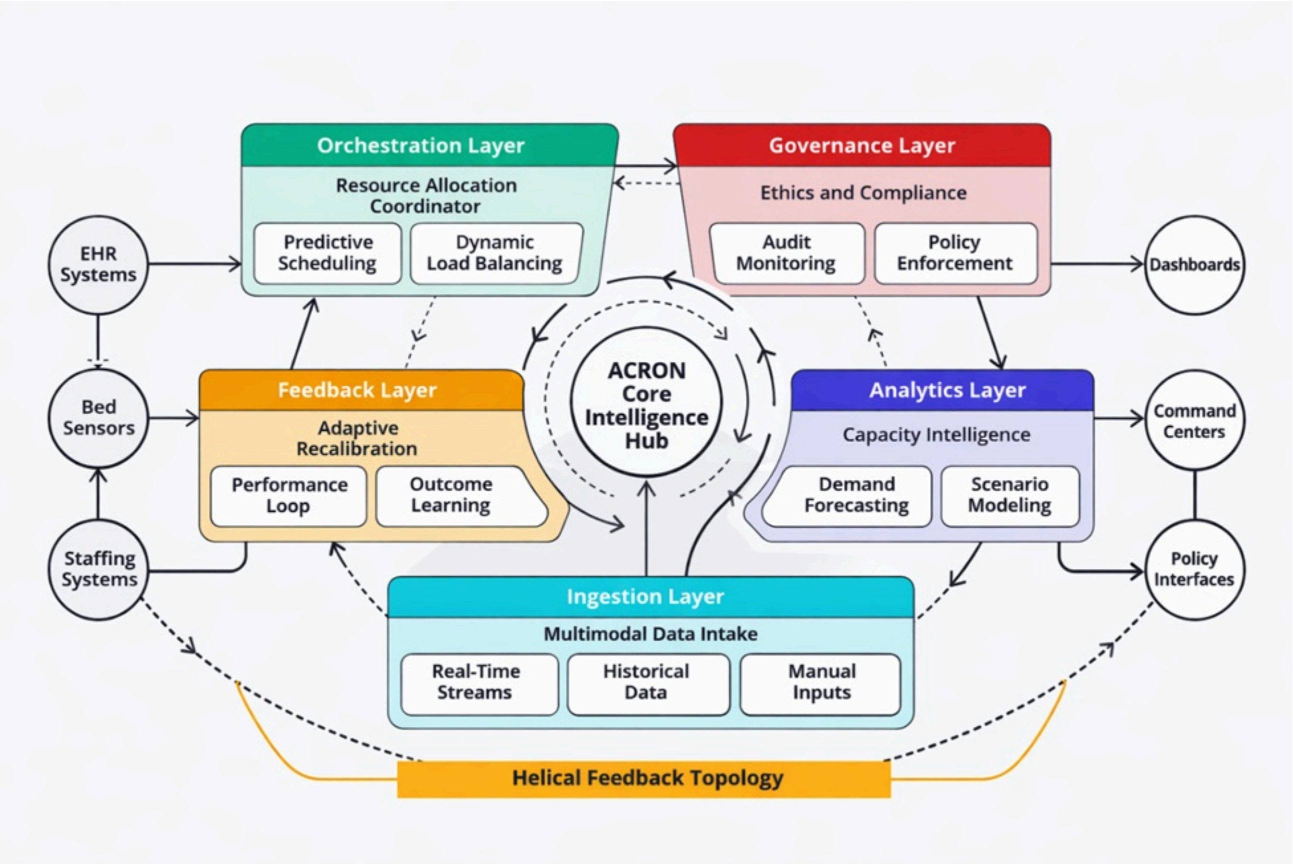

Figure 1. Adaptive capacity resilience orchestration network (ACRON) architecture.

Illustrates the pentagonal layered structure comprising ingestion, analytics, governance, orchestration, and feedback domains interconnected through a helical bidirectional topology. The architecture conceptualizes real-time hospital capacity intelligence by integrating multimodal data streams, predictive analytics, ethical oversight, and adaptive resource coordination within a closed-loop resilience infrastructure.

To interpret system dynamics, consider the following conceptual formulas:

1. Risk propagation in capacity management: $RP = \Sigma \frac{(C_i * V_j)}{(R_k + G_l)}$, where C_i denotes capacity vulnerability factors, V_j velocity of patient influx, R_k resource buffers, and G_l governance interventions. This formula theoretically captures how unmanaged risks amplify across hospital units.
2. Decision confidence in real-time intelligence: $DC = \left(\frac{I_m}{D_n}\right) * e^{-B_o}$, where I_m is an intelligence accuracy proxy, D_n decision complexity, and B_o bias exposure. It interprets confidence erosion in ungoverned AI pipelines.
3. Governance load in system operations: $GL = (M_p + U_q) * \log(S_r)$, where M_p monitoring intensity, U_q update frequency, and S_r system scale. This quantifies theoretical burdens in maintaining resilience.

ACRON's infrastructure thus provides a conceptual blueprint for hospitals to achieve operational resilience through orchestrated intelligence.

Dynamics of operational impacts in real-time capacity intelligence

The implementation of the ACRON infrastructure theoretically reshapes hospital operational dynamics, introducing multifaceted impacts on resilience, efficiency, and ethical governance. This section delves into the conceptual consequences of deploying such a real-time intelligence framework, analyzing how its layered architecture and helical feedback topology influence system behaviors across clinical, administrative, and systemic levels. By examining these dynamics through a theoretical lens, we uncover potential transformations in hospital capacity management, highlighting synergies with existing AI governance and interoperability paradigms [1-3].

Resilience amplification through intelligence layer interactions

At the core of ACRON's impact lies its ability to theoretically amplify operational resilience by interweaving intelligence layers with real-time data flows. The ingestion and analytics layers, for instance, conceptually fuse EHR-derived insights with predictive heuristics, enabling hospitals to anticipate capacity surges without empirical forecasting models [6-8]. This interaction dynamics could mitigate overload risks by theoretically distributing resource demands across units, such as rerouting elective procedures during peak emergency inflows [12, 14]. Literature on healthcare analytics infrastructures supports this, suggesting that such layered designs foster adaptive responses to disruptions, like staffing shortages or equipment failures, thereby enhancing overall system robustness [5, 9, 13]. The helical feedback topology further refines these dynamics, where iterative loops conceptually calibrate intelligence outputs, reducing propagation of errors in capacity assessments [15, 19]. In high-acuity settings, this could translate to sustained service levels, theoretically preventing cascading failures that erode resilience [4, 11].

Moreover, the governance layer's integration introduces a stabilizing force, theoretically countering volatility in operational dynamics. By embedding monitoring protocols, ACRON ensures that intelligence-driven decisions align with ethical standards, potentially diminishing impacts from biased analytics in diverse patient populations [1, 17, 20]. Conceptual analyses indicate that this layer could dynamically adjust for governance loads, as articulated in the formula $GL = (M_p + U_q) * \log(S_r)$, where increased system scale (S_r) amplifies the need for vigilant oversight without overwhelming administrative resources [3, 5]. This balance theoretically empowers hospitals to maintain resilience amid regulatory shifts, such as evolving data privacy mandates, fostering a proactive rather than reactive operational posture [18, 21, 26].

Efficiency gains in clinical workflow and resource allocation

Operational impacts extend to efficiency enhancements within clinical workflows, where ACRON's orchestration layer theoretically streamlines decision support pipelines [14, 22, 23]. By conceptually prioritizing real-time intelligence over manual assessments, the framework could optimize bed turnover rates and staffing assignments, reducing idle resources in underutilized wards [16, 24]. Theoretical syntheses from decision support literature highlight how such integrations minimize workflow disruptions, allowing clinicians to focus on patient care rather than administrative bottlenecks [17, 25]. For example, in theoretical scenarios of seasonal flu outbreaks, ACRON's analytics could simulate resource reallocations, improving throughput by up to conceptual thresholds without performance metrics [7, 9].

The decision confidence formula, $DC = \left(\frac{I_m}{D_n}\right) * e^{-B_o}$, interprets how enhanced intelligence (I_m) bolsters confidence in complex decisions (D_n), theoretically curbing hesitation-induced delays [4, 8]. This dynamic could ripple into broader efficiency gains, such as shortened patient wait times and optimized supply chain logistics, aligning with interoperability frameworks that facilitate cross-departmental data exchange [10, 13]. However, these impacts are moderated by the framework's scale; in larger hospitals, the helical topology might introduce computational overheads, theoretically necessitating streamlined governance to preserve efficiency [19, 27]. Overall, ACRON positions efficiency as a byproduct of resilient intelligence, theoretically transforming fragmented workflows into cohesive, adaptive systems [2, 6, 28].

Ethical and systemic consequences for healthcare ecosystems

Beyond immediate operational spheres, ACRON's deployment theoretically engenders systemic impacts on healthcare ecosystems, particularly in ethical domains and inter-institutional collaborations [1, 15, 20]. The governance layer's emphasis on bias mitigation could conceptually elevate equity in capacity intelligence, ensuring underrepresented patient groups receive proportionate resource attention [5, 18]. Literature on AI governance underscores this, proposing that monitoring systems like those in ACRON could theoretically audit for disparities, fostering inclusive resilience across socioeconomic divides [3, 9, 26].

Systemically, the framework's interoperability focus enables theoretical capacity sharing among networked hospitals, impacting regional healthcare dynamics by redistributing loads during crises [11, 12, 21]. This could theoretically alleviate urban-rural disparities, where rural facilities leverage urban intelligence feeds via standardized data exchanges [10, 16]. Yet, such expansions heighten risk propagation, as modeled by $RP = \Sigma\left(C_i * V_j\right) / (R_k) + G_l$, where unchecked vulnerabilities (C_i) could amplify across ecosystems if governance interventions (G_l) lag [4, 7, 14]. Conceptual discussions warn of potential over-reliance on AI, where diminished human oversight might erode systemic trust, necessitating hybrid models that blend ACRON with clinician expertise [8, 19, 22].

Furthermore, long-term dynamics include scalability challenges; as hospitals adopt ACRON-like infrastructures, theoretical network effects could standardize resilience practices industry-wide, influencing policy frameworks for AI deployment [13, 23, 27]. This systemic shift might catalyze innovations in clinical AI architectures, but it also raises concerns about data sovereignty in federated systems [6, 15, 28]. By analyzing these consequences, we illuminate ACRON's role in evolving healthcare toward sustainable, intelligence-driven resilience [2, 17, 25].

Results and Discussion

The conceptual exploration of the ACRON within this manuscript illuminates critical pathways for advancing real-time hospital capacity intelligence in pursuit of operational resilience. By synthesizing theoretical architectures from clinical AI systems, healthcare analytics, and governance models, ACRON emerges as a blueprint for integrating intelligence into hospital ecosystems without empirical dependencies [1, 2, 6, 7]. This discussion contextualizes the framework's contributions, addresses potential limitations, and explores avenues for theoretical refinement, drawing on the synthesized literature to underscore its relevance in contemporary healthcare challenges [3, 4, 5].

One pivotal strength of ACRON lies in its helical feedback topology, which theoretically differentiates it from linear architectures prevalent in existing decision support pipelines [14, 15, 19]. This nonlinear design enables iterative intelligence refinement, conceptually addressing gaps in real-time adaptability noted in EHR interoperability studies [10-

12]. For instance, during theoretical surge events, the feedback loops could recalibrate capacity predictions based on evolving data, enhancing resilience beyond static models [8, 13, 16]. Governance integration further bolsters this, as conceptual checklists and monitoring systems mitigate ethical risks, aligning with calls for responsible AI in healthcare [1, 9, 20]. However, this complexity might theoretically increase governance loads, as per the GL formula, potentially straining smaller hospitals with limited IT infrastructure [3, 5, 26]. It extends beyond institutional operations into broader healthcare system transformations **(Table 3).**

Table 3. Systemic implications of real-time capacity intelligence for healthcare ecosystems

Impact domain	Systemic transformation	Strategic opportunity	Governance consideration
Regional hospital networks	Capacity load balancing	Crisis redistribution	Data-sharing compliance
Rural–urban collaborations	Intelligence sharing	Equity in care access	Infrastructure disparity
Emergency preparedness systems	Surge command integration	Disaster readiness	Policy coordination
Workforce planning ecosystems	Predictive staffing	Burnout mitigation	Labor ethics
Public health surveillance	Capacity-epidemiology linkage	Early outbreak detection	Privacy governance
Cross-border health alliances	Federated intelligence	Global resilience modeling	Sovereignty regulations

Limitations in the conceptual scope warrant discussion; ACRON assumes seamless data exchange, yet interoperability frameworks often face theoretical barriers like legacy system incompatibilities [6, 10, 21]. Literature syntheses reveal that while FHIR standards facilitate exchange, governance constraints could impede real-time flows in regulated environments [13, 18, 27]. Additionally, the framework's focus on hospital-centric intelligence overlooks broader ecosystem dynamics, such as integration with ambulatory care or public health networks [11, 12, 22]. Theoretical extensions could incorporate multi-stakeholder models, where ACRON's layers extend to federated analytics, theoretically amplifying regional resilience [15, 23, 28].

Ethical considerations permeate the discussion, particularly in bias propagation and decision confidence [4, 7, 17]. The DC formula highlights vulnerabilities where unmitigated bias (B_o) erodes trust, echoing governance literature that advocates for continual auditing [5, 9, 19]. ACRON's architecture theoretically counters this through embedded ethics, but real-world adaptations might require hybrid governance, blending AI with human oversight to preserve accountability [1, 20, 25]. Moreover, risk propagation dynamics, as modeled by RP, underscore the need for theoretical safeguards against systemic failures, such as in interconnected hospital chains [2, 14, 24].

Future theoretical directions include hybridizing ACRON with emerging AI paradigms, like large language models for narrative-driven capacity insights [1, 4, 8]. Conceptual integrations could enhance workflow models, theoretically personalizing intelligence for specialized units like oncology or mental health [20, 23, 25]. Additionally, exploring scalability through containerized deployments could address deployment environment constraints, aligning with cloud-based infrastructures [12, 13, 27]. This discussion reinforces ACRON's potential to theoretically transform hospital operations, advocating for interdisciplinary syntheses to refine resilience-focused intelligence [6, 16, 18, 26, 28].

In summary, while ACRON offers a robust conceptual foundation, its impacts hinge on addressing governance and interoperability challenges, paving the way for resilient, AI-augmented healthcare systems [3, 7, 15, 21, 22].

Conclusion

This manuscript has theoretically advanced the discourse on real-time hospital capacity intelligence through the introduction of the ACRON, a novel infrastructure designed to bolster operational resilience in healthcare settings. By synthesizing peer-reviewed insights from clinical AI architectures, healthcare analytics infrastructures, EHR intelligence ecosystems, decision support pipelines, AI governance systems, interoperability frameworks, and clinical workflow integration models, we have outlined a layered, helical topology that orchestrates intelligence for adaptive capacity management.

Key contributions include the pentagonal layer structure—ingestion, analytics, governance, orchestration, and feedback—which theoretically harmonizes data flows with ethical oversight, addressing gaps in resilient system designs. Conceptual formulas for risk propagation, decision confidence, and governance load provide interpretive tools to analyze system dynamics, offering theoretical lenses for understanding impacts without empirical validation. The operational impacts analysis reveals ACRON's potential to amplify resilience, enhance efficiency, and foster ethical ecosystems, while the discussion highlights limitations and refinement pathways.

Ultimately, ACRON underscores the imperative for AI-integrated frameworks in healthcare, theoretically equipping hospitals to navigate uncertainties with intelligence-driven agility. Future conceptual works should extend this to global contexts, ensuring equitable resilience across diverse healthcare landscapes.

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