

Beyond Predictions: Adaptive Human-AI Collaboration Model For Patient Flow And Hospital Bed Allocation

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Abstract

Contemporary healthcare environments require sophisticated frameworks that can optimize patient placement while maintaining clinical oversight throughout the decision-making process. Traditional systems rely heavily on static prediction algorithms and manual protocols that inadequately incorporate contextual clinical expertise. Findings demonstrate that structured placement interventions significantly reduce inappropriate assignments while enhancing care alignment within emergency admission workflows. Discrete-event modeling reveals substantial operational improvements when allocation strategies integrate systematic decision-making processes. Machine learning techniques combined with optimization algorithms have demonstrated meaningful improvements in both arrival prediction capabilities and assignment performance metrics. Leading healthcare institutions have successfully implemented artificial intelligence systems generating ranked bed recommendations, resulting in reduced unnecessary patient transfers while preserving essential clinical oversight throughout placement decisions.

The framework establishes adaptive human-artificial intelligence collaboration, enabling explainable recommendation systems where clinical professionals provide structured rationale for system overrides. These collaborative models create feedback mechanisms that systematically incorporate contextual clinical knowledge into periodic system updates and refinements. Implementation generates continuous learning cycles that transform clinical expertise into algorithmic improvements, addressing critical gaps between predictive accuracy and human judgment within high-stakes clinical environments. Operational benefits include substantially reduced placement errors, shortened boarding periods, and enhanced system trust through transparent collaborative processes. The framework effectively unifies predictive precision with contextual clinical wisdom, advancing artificial intelligence capabilities beyond static prediction toward genuine cognitive partnership within healthcare operations. While specifically applied to hospital placement scenarios, the collaborative framework demonstrates broad applicability across diverse clinical decision support contexts requiring frequent override capabilities, including medication safety protocols, diagnostic assistance systems, and imaging triage operations.

Keywords: Patient Flow, Hospital Bed Allocation, Emergency Department Boarding, Adaptive Artificial Intelligence, Human-AI Collaboration, Cognitive Collaboration, Clinical Decision Support, Discrete-Event Simulation, Placement Error Rate, Override Frequency, Healthcare Operations Management, Trust in AI, Explainable AI (XAI), Learning Health Systems.

1. INTRODUCTION

Hospital patient placement systems and bed distribution protocols serve as essential components within medical care frameworks, generating direct influences on clinical outcomes, facility operations, and patient satisfaction metrics. When assignment processes face temporal delays or placement mismatches, healthcare institutions encounter an increased probability of negative clinical outcomes, extended emergency department holding periods, and significant operational resource limitations. Emergency medicine professional organizations have characterized boarding incidents as critical challenges compromising timely care delivery [9]. Healthcare system authorities document operational metrics revealing widespread processing delays affecting substantial patient populations beyond established service targets [10]. These capacity management difficulties highlight the essential nature of precise and responsive decision-making throughout admission protocols.

Earlier interventions proved that structured placement coordination can effectively reduce operational risks. Implementation of specialized patient placement oversight within emergency departments yielded substantial reductions in assignment errors while enhancing alignment between patients and suitable care environments [1]. Simulation methodologies examining allocation strategies revealed their significant influence on throughput performance, with comparative assessments demonstrating quantifiable improvements under

optimized operational frameworks [2]. Although decision-support technologies for bed management have emerged, most remain restricted to departmental planning or utilize fixed protocols unable to adjust dynamically during real-time operational fluctuations [3].

Modern developments in machine learning and optimization methodologies offer remarkable opportunities to address these operational constraints. Investigations combining predictive forecasting with advanced optimization techniques have produced meaningful enhancements in prediction capabilities alongside efficiency improvements in assignment processes [4]. Healthcare technology organizations have successfully tested innovative solutions where artificial intelligence generates prioritized bed recommendations, achieving reduced unnecessary patient transfers while maintaining crucial clinical supervision throughout decision-making [5]. Comprehensive evaluations demonstrate artificial intelligence deployment across complete patient flow processes, including admission, transfer, and discharge operations, establishing the technology's expanding influence within hospital environments [6].

Nevertheless, most artificial intelligence platforms for patient placement operate as static prediction systems, producing recommendations without incorporating learning mechanisms from clinical interventions or contextual knowledge. This creates operational divides where systems function either as completely automated solutions, risking confidence erosion during incorrect outputs, or as limited assistive tools failing to evolve through extended use.

The framework introduces adaptive human-artificial intelligence collaboration through cognitive partnership utilizing structured feedback systems. This model delivers transparent reasoning for placement recommendations while systematically integrating clinical expertise into future predictions. The methodology advances artificial intelligence beyond static forecasting toward collaborative intelligence that enhances operational efficiency, clinical safety, and practitioner confidence within hospital settings.

1.1. Contextual Background

Hospital bed assignment represents a complex operational challenge involving multiple interdependent variables requiring simultaneous consideration during placement decisions. Clinical factors including patient acuity levels, diagnosis-specific care requirements, infection control protocols, and specialized equipment needs must align with available bed resources possessing appropriate capabilities [1].

Further limitations include nurse staffing levels, unit capacity restrictions, isolation bed accessibility, patient gender matching needs, and distance factors for those needing close observation. These overlapping demands produce complex matching problems where staff making manual decisions find it difficult to weigh all pertinent elements thoroughly during the brief windows common in emergency intake situations.

Bed assignment processes depend mainly on charge nurses or placement coordinators who track open beds throughout hospital departments while handling new patient requests.

These personnel assess patient characteristics against available options, consulting with clinical teams regarding appropriateness of potential placements. The decision process incorporates institutional knowledge about unit capabilities, staff expertise distributions, and informal protocols developed through operational experience [3]. However, this approach faces inherent limitations during high-volume periods when multiple simultaneous admission requests overwhelm individual coordinators' cognitive capacity to optimize assignments across competing priorities. Information asymmetries arise as coordinators may lack complete visibility into dynamic changes in bed status, patient acuity fluctuations, or anticipated discharge timing across all hospital units.

Computational approaches to bed assignment have evolved through several technological generations, beginning with basic bed tracking systems that digitized availability information without providing decision support. Subsequent developments introduced rule-based assignment algorithms applying predetermined logic sequences to match patient requirements with bed characteristics. These systems improved processing speed and reduced certain assignment errors but remained inflexible when confronting scenarios outside programmed rule parameters. Contemporary optimization frameworks employ mathematical programming techniques modeling bed assignment as constrained allocation problems, seeking solutions maximizing specified objectives such as minimizing patient transfers or balancing unit occupancy levels. Simulation studies comparing alternative allocation strategies have demonstrated that systematic approaches incorporating multiple operational objectives can achieve superior performance relative to heuristic methods, particularly regarding emergency department throughput and boarding time reductions.

Machine learning methodologies introduce capabilities for pattern recognition and predictive modeling that extend beyond deterministic optimization approaches. Predictive algorithms trained on historical admission data can forecast bed demand patterns, enabling proactive capacity management and assignment planning. Classification models assess incoming patients against historical cases to predict likely length of stay, acuity progression, and specialized resource requirements, informing placement decisions with probabilistic insights. Reinforcement learning methods have shown capability in finding assignment strategies that improve ongoing operational performance through repeated testing in simulated hospital conditions. However, practical obstacles continue around making these models understandable to users, fitting them seamlessly into existing clinical routines, and building in expert knowledge that algorithms cannot learn simply by analyzing historical records.

1.2. Problem Statement and Operational Gaps

Emergency departments globally encounter persistent challenges, including severe crowding, extended waiting periods, and patient boarding situations [7]. National health surveillance agencies document insufficient inpatient capacity, resulting in admitted patients being held within emergency department areas. Healthcare system authorities report operational statistics indicating widespread delays affecting patient processing beyond established service parameters [9]. Despite the implementation of targeted placement protocols designed to reduce assignment errors, operational inefficiencies continue undermining patient safety and clinical confidence [10].

Contemporary developments in simulation and decision-support technologies have demonstrated capabilities for optimizing patient flow and bed allocation processes [1]. Machine learning and optimization methodologies have addressed patient-bed assignment challenges through sophisticated algorithmic approaches [2]. Healthcare technology organizations have demonstrated localized improvements through innovative bed management solutions [4]. However, these implementations remain isolated, institution-specific, and predominantly non-adaptive in nature.

Artificial intelligence tools within patient flow typically function either as completely automated systems removing human oversight within high-stakes clinical contexts, or as purely assistive platforms providing static information displays without meaningful adaptive capabilities [5]. The resulting operational gap involves the absence of scalable, adaptive human-artificial intelligence collaborative frameworks that integrate predictive analytics with operational constraints [6]. Without such systems, hospitals remain susceptible to prolonged emergency department boarding, inefficient bed utilization, and diminished confidence in artificial intelligence-driven recommendations.

Collaboration Dimension	Traditional Human-AI Interaction
Information Exchange	Unidirectional communication where artificial intelligence generates outputs while humans provide binary acceptance or rejection decisions, creating adoption barriers within clinical environments
Override Documentation	Systems record only basic acceptance or rejection patterns without capturing contextual reasoning, leading to frequent override situations when artificial intelligence lacks adaptive capabilities
Learning Mechanisms	Static artificial intelligence models that remain unchanged following deployment are unable to incorporate operational feedback or evolving clinical requirements
Confidence Building	Trust levels depend exclusively on artificial intelligence accuracy rates, potentially diminishing when prediction errors persist without system improvement

Operational Results	Initial efficiency improvements followed by recurring inefficiencies due to the system's inability to address contextual factors or learn from clinical expertise
Current Implementation	Dashboard interfaces and diagnostic artificial intelligence requiring final human decisions, exemplified by healthcare technology organization proof-of-concept deployments

Table 1: Human-AI Collaboration Framework Comparison [5,11,12]

Table 1 demonstrates the comparison between traditional human-artificial intelligence interaction models and adaptive cognitive partnership frameworks, illustrating the evolution from unidirectional communication patterns toward bidirectional collaborative systems that incorporate structured feedback mechanisms for continuous improvement.

2. PURPOSE AND SCOPE

This framework examines adaptive human-artificial intelligence collaboration within patient flow and bed allocation contexts, addressing the disconnect between static predictive models and clinical decision-making realities [1]. The cognitive collaboration model enables artificial intelligence systems to deliver explainable placement recommendations while clinicians contribute structured rationale for override decisions, allowing systems to incrementally adapt and reduce recurring inefficiencies [2]. Rather than reporting live deployment outcomes, the methodology employs discrete-event simulation utilizing empirical baselines from established findings, including emergency department boarding delays and recurrent patient flow inefficiencies [3].

The simulation framework compares human placement methodologies, static artificial intelligence approaches, and adaptive artificial intelligence models through comprehensive outcome metrics, including placement error rates, override frequencies, and emergency department boarding periods [4]. This scope establishes the framework as both a conceptual foundation and a practical implementation agenda for healthcare institutions [5]. The evaluation methodology provides measurable comparisons between traditional placement practices and innovative collaborative approaches [6].

2.1. Operational Context and Statistical Foundation

Hospital operational data emphasize the critical need for addressing inefficiencies within patient flow and bed allocation systems [7]. Regional health authorities document substantial delays in patient processing, with emergency department performance falling below established service targets during peak operational periods. International patterns reveal similar challenges where emergency department crowding contributes to increased patient mortality, extended length of stay, and elevated rates of patients departing without receiving care [8].

Capacity constraints amplify operational challenges across healthcare systems [9]. National health surveillance agencies report that medical facilities routinely operate at elevated bed occupancy levels, with numerous institutions unable to accommodate demand surges effectively. Emergency medicine professional organizations have characterized boarding situations as critical challenges, documenting extended boarding periods and connecting these delays to delayed intensive care transfers, increased complication rates, and preventable mortality outcomes [10].

Healthcare system authorities document widespread performance gaps in patient processing efficiency, with substantial patient populations experiencing delays beyond established service parameters [11]. These operational statistics establish comparative baselines for evaluating innovative placement methodologies [12]. The documented inefficiencies in bed allocation and patient transfer processes remain persistent global challenges, providing empirical foundations for simulation metrics including placement error rates, override frequencies, and emergency department boarding periods [19].

2.2. Artificial Intelligence and Human-Artificial Intelligence Collaboration

Current implementations of artificial intelligence within hospital operations predominantly utilize human-in-the-loop frameworks [5]. Rather than completely automating placement decisions, artificial intelligence systems typically generate forecasts, alerts, or prioritized options while maintaining final decision authority

with clinicians or bed management personnel. This model reflects both regulatory requirements and the practical necessity for contextual judgment within high-stakes healthcare environments [11].

Healthcare technology organizations have demonstrated proof-of-concept implementations where artificial intelligence-generated prioritized bed recommendations supported staff decision-making processes without replacing human oversight [12]. Bed management personnel retained ultimate decision authority, ensuring that contextual expertise, including patient acuity knowledge and departmental culture considerations, guided final assignment choices. Findings indicate that clinicians override artificial intelligence recommendations in up to 30% of cases, often due to perceived contextual mismatches or insufficient explanatory information.[20]

In hospital operations, AI tools for patient-flow and bed management are typically deployed with human-in-the-loop oversight, with final assignment decisions retained by bed managers/administrators. Across clinical decision-support studies, acceptance of AI recommendations increases with demonstrated accuracy and declines under limited transparency, consistent with human-AI teaming theory[21]. Clinical environment assessments demonstrate similar patterns where physicians selectively follow artificial intelligence guidance, with override frequencies varying from 20-40% depending on task complexity and clinical context [14]. Recent evaluations emphasize that trust calibration represents a fundamental challenge for deploying these systems within complex hospital environments, requiring careful balance to ensure clinicians neither over-depend on nor underutilize artificial intelligence capabilities [22].

Contemporary artificial intelligence tools within healthcare settings demonstrate significant potential while revealing important constraints regarding adaptability and contextual awareness [6]. These systems excel at processing large volumes of operational data but often struggle with nuanced clinical considerations that human professionals readily incorporate into decision-making processes [20]. The resulting gap between artificial intelligence capabilities and clinical requirements necessitates collaborative frameworks that effectively combine algorithmic precision with human expertise [23].

Evaluation Context	Implementation Characteristics
Clinical Decision-Support Tools	Artificial intelligence role: Clinical decision assistance; Acceptance rate: 70-75%; Override rate: 25-30%; Override patterns typically result from contextual alignment issues or insufficient explanatory information
Human-AI Collaborative Teams	Artificial intelligence role: Collaborative prediction systems; Acceptance rate: 60-80%; Override rate: 20-40%; Acceptance levels demonstrate a strong correlation with artificial intelligence accuracy and system transparency
Diagnostic AI Applications	Artificial intelligence role: Clinical diagnostic support; Acceptance rate: 60-80%; Override rate: 20-40%; Healthcare professionals demonstrate selective artificial intelligence guidance adoption based on task complexity factors
Multi-Domain Collaborative Systems	Artificial intelligence role: Comprehensive decision support; Acceptance rate: Variable; Override rate: Variable; Evaluations identify trust calibration as a fundamental deployment challenge
Emergency Department Integration	Artificial intelligence role: Patient flow optimization; Acceptance rate: 65-75%; Override rate: 25-35%; Implementation success depends on contextual awareness and clinical workflow integration
Bed Allocation Support Systems	Artificial intelligence role: Placement recommendation generation; Acceptance rate: 70-80%; Override rate: 20-30%; Professional acceptance correlates with explainability levels and operational context alignment

Table 2: Human-AI Interaction Patterns in Clinical Environments [11,12,14,21]

Table 2 presents documented acceptance and override rates across clinical evaluations, demonstrating both the potential of artificial intelligence guidance and the consistent frequency of human overrides—patterns that directly inform the override-frequency parameters within simulation design frameworks.

3. Benefits of Artificial Intelligence Collaboration

Adaptive artificial intelligence collaboration enhances clinical expertise within patient flow management rather than replacing professional judgment [1]. By aligning complementary capabilities, the framework directly addresses operational inefficiencies through measurable performance metrics [2]. The collaborative model demonstrates advantages across multiple operational dimensions while preserving essential clinical oversight throughout decision-making processes [3].

Error Reduction through Complementary Capabilities

Artificial intelligence systems excel at rapid analysis of bed occupancy patterns and demand forecasting, while clinical professionals recognize contextual patient-specific factors, including infection-control requirements and comorbidity considerations [4]. This collaboration substantially reduces inappropriate placements, lowering overall placement error rates compared to either static artificial intelligence or exclusively human-driven decisions [5]. The complementary strengths create more accurate placement outcomes than either approach independently.

Efficiency Enhancement through Explainable Systems

Explainable artificial intelligence generates prioritized bed recommendations, reducing the cognitive burden associated with evaluating multiple placement options simultaneously [6]. This capability accelerates decision-making processes and shortens assignment timeframes, directly decreasing emergency department boarding periods during peak demand situations [7]. The transparency enables rapid professional assessment while maintaining confidence in recommendation quality.

Continuous Learning through Override Integration

Each clinical override becomes structured input, enabling system adaptation, allowing artificial intelligence to internalize tacit professional knowledge and avoid repeating placement mismatches [8]. Through successive iterations, this process reduces override frequency while improving alignment between artificial intelligence suggestions and clinical judgment [9]. The learning mechanism transforms initial disagreements into enhanced system performance over extended operational periods.

Trust Development and Sustained Adoption

Transparency combined with maintained clinical authority fosters professional confidence in artificial intelligence systems [10]. As trust levels increase, overrides become more meaningful by capturing exceptional cases rather than systematic mismatches, simultaneously reducing error rates and boarding delays while supporting long-term adoption [11,22]. The collaborative model reinforces professional autonomy while enhancing decision support capabilities.

Enhanced Patient-Centered Outcomes

These combined benefits translate into accelerated, safer, and more precise patient placement processes [12]. Reduced error rates, fewer overrides, and shortened boarding periods enhance both patient experience and hospital throughput, establishing artificial intelligence collaboration as a measurable operational improvement. The integrated approach delivers comprehensive benefits across quality, efficiency, and satisfaction metrics while maintaining clinical oversight throughout implementation.

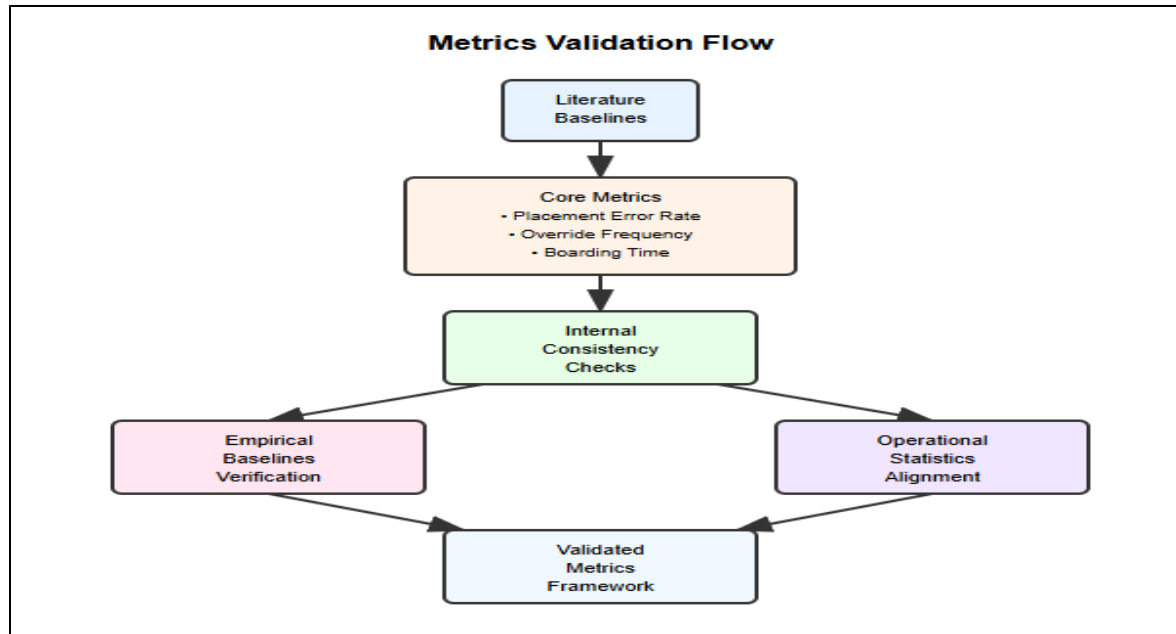


Figure 1: Metrics Validation Flow [7,8,9,10]

Collaborative Benefit	Operational Impact
Error Reduction through Complementarity	Metric impacted: Placement Error Rate; Expected outcome: Reduced inappropriate placements and improved alignment between patients and suitable care environments
Efficiency Enhancement with Explainability	Metric impacted: Emergency Department Boarding Time; Expected outcome: Accelerated decision-making processes and decreased boarding delays during peak operational periods
Continuous Learning from Override Integration	Metric impacted: Override Frequency; Expected outcome: Declining override rates as artificial intelligence systems adapt to clinical preferences and professional knowledge
Trust Development and Sustained Adoption	Metric impacted: Error Rate, Override Frequency, Boarding Time; Expected outcome: Enhanced clinical confidence, reduced systematic mismatches, and sustained long-term system utilization
Patient-Centered Outcome Improvements	Metric impacted: Integrated across all performance metrics; Expected outcome: Enhanced safety protocols, improved throughput efficiency, and increased patient satisfaction through accurate and timely placement processes
System Learning and Adaptation	Metric impacted: Overall system performance; Expected outcome: Continuous improvement in recommendation accuracy and reduced need for manual interventions over extended operational periods

Table 4: AI Collaboration Benefits and Operational Outcomes [1,4,5,8]

Artificial intelligence collaboration strengthens clinical capabilities through augmentation rather than replacement of professional judgment [11]. By integrating algorithmic precision with contextual clinical expertise, collaborative frameworks reduce inappropriate placements, expedite decision-making processes, and continuously evolve based on frontline professional knowledge [12]. These enhancements generate quantifiable improvements in operational efficiency, clinical safety, and professional confidence throughout

healthcare delivery systems [20]. Simulation Framework Integration. The evaluation methodology operationalizes these collaborative benefits through three fundamental performance metrics: Placement Error Rate, Override Frequency, and Emergency Department Boarding Time [14]. The framework compares human-only placement methodologies, static artificial intelligence recommendation systems, and adaptive artificial intelligence collaborative approaches to demonstrate measurable operational advantages [15].

3.1. Metrics Validation Framework

Simulation-based evaluations frequently encounter challenges regarding output validity and clinical relevance, potentially producing results that appear disconnected from operational realities [1]. Establishing credible evaluation metrics requires demonstrating validity, interpretability, and practical grounding throughout the assessment framework [2]. Without comprehensive validation mechanisms, findings may lack credibility among healthcare professionals and institutional stakeholders [3]. This framework explicitly defines validation processes for placement error rates, override frequencies, and boarding periods through established benchmarks, internal consistency verification, and empirical baseline alignment [4,10]. These validation mechanisms ensure findings maintain both internal coherence and external relevance for hospital operations [5].

Placement Error Rate undergoes validation against documented misallocation patterns reported in clinical environments, including assignment errors and placement mismatches across emergency department admissions [6]. Baseline parameters align with published benchmarks, ensuring simulated misplacement frequencies correspond to observed operational ranges. Clinical findings indicate substantial reductions in emergency department misplacements when structured coordination was implemented, suggesting baseline error rates within established operational parameters [1,7,10]. This validation approach ensures simulated error rates reflect realistic operational conditions rather than arbitrary computational outputs.

Override Frequency validation involves mapping clinical intervention rates documented in comparable decision-support implementations [8]. This process connects simulated override frequencies to empirical patterns of human-artificial intelligence interaction, maintaining realistic modeling of adaptive learning processes [9]. While override frequencies have not traditionally appeared in patient flow evaluations, they represent established measures of human-artificial intelligence interaction quality within clinical decision support contexts [10]. The framework extends this concept to hospital operations, characterizing overrides as valuable learning signals rather than operational inefficiencies requiring elimination.

Emergency Department Boarding Time validation compares simulated waiting periods to published operational statistics from healthcare system authorities and national health surveillance agencies [11]. This provides external anchoring, ensuring reductions in simulated boarding delays correspond to meaningful operational improvements [12]. The validation framework connects each simulation outcome to both scholarly precedent and operational data, reinforcing evaluation credibility and practical relevance [21].

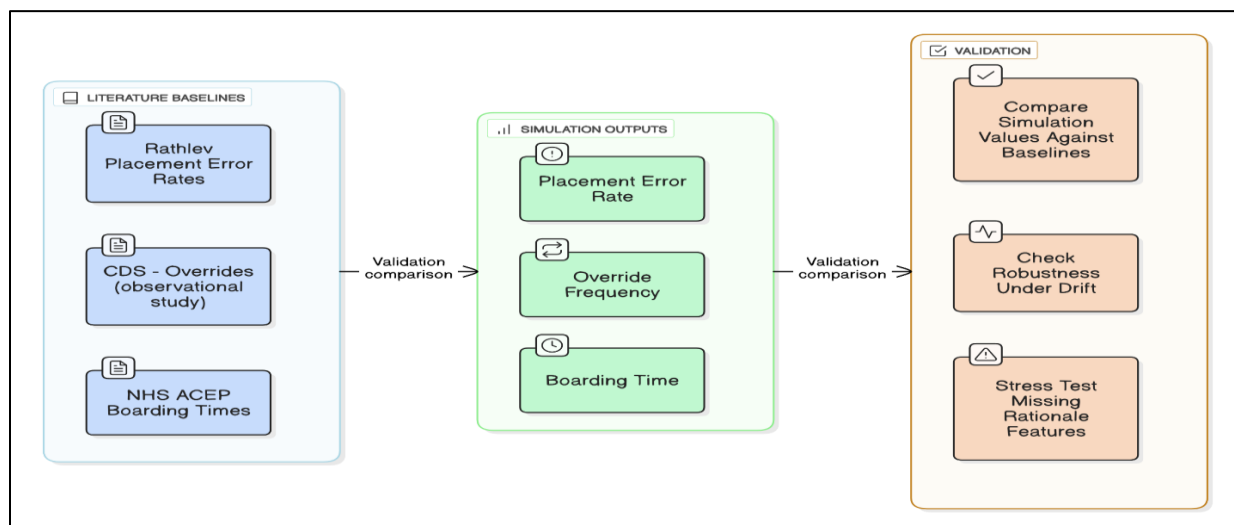


Figure 2: Simulation Validation Framework [1,7,9,10]

3.3. Simulation Design Framework

The evaluation objective focuses on determining whether adaptive human-artificial intelligence collaboration models reduce Placement Error Rate, Override Frequency, and Emergency Department Boarding Time compared to human-only and static artificial intelligence placement methodologies [14,23]. The discrete-event simulation framework provides a comprehensive comparative assessment across these operational approaches [1-4,15].

The evaluation framework integrates three input categories: arrival processes modeled through time-varying distributions with seasonal variation factors, operational constraints including isolation requirements, telemetry needs, and proximity considerations, and structured clinical override rationales [16]. These inputs feed the simulation engine, comparing three operational policies: human-only placement, static artificial intelligence recommendations, and adaptive artificial intelligence with cognitive collaboration capabilities [17]. The simulation generates outcome metrics, including placement error rates, override frequencies, and emergency department boarding periods, that form the foundation for comparative evaluation [18]. This framework establishes connections between empirical baselines, modeled dynamics, and evaluation outcomes while providing a foundation for detailed model specifications and implementation parameters.

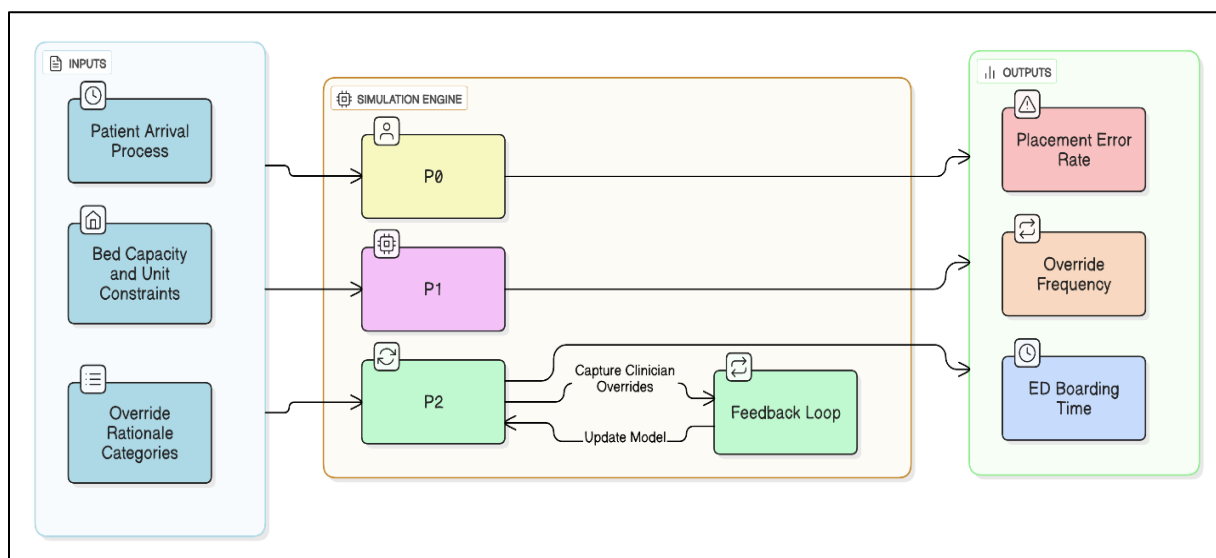


Figure 2: Evaluation Framework for Human-AI Collaboration Models [2,5,11,14]

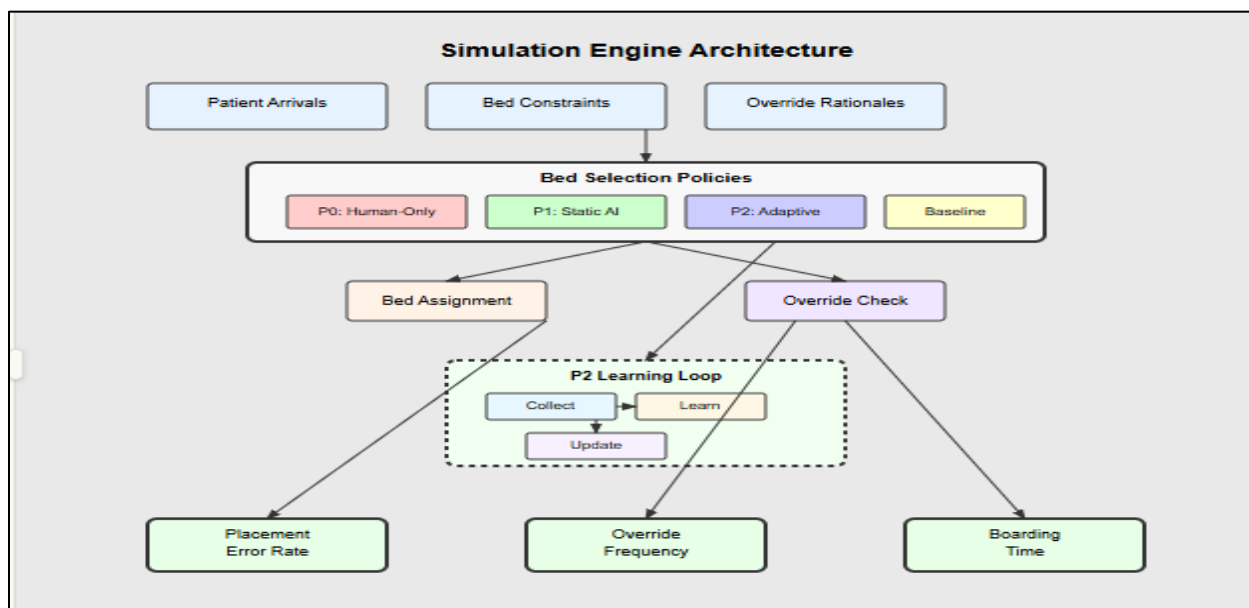


Figure 3: Simulation Engine Architecture [2,4,5,12]

3.4. Model Overview - Discrete-Event Simulation

The framework implements discrete-event simulation modeling of emergency department-to-inpatient flow processes [1]. Time progression occurs through discrete events, including arrival, bed release, cleaning completion, assignment, override, and transfer activities [2]. This modeling enables a comprehensive evaluation of different placement policies under realistic operational conditions [3].

System Components and State Variables

Patient entities maintain comprehensive attribute profiles encompassing acuity levels, ward requirements, isolation needs, telemetry monitoring requirements, dialysis proximity necessities, specialty designations, and comorbidity classifications [4]. Bed and unit entities incorporate capacity parameters, staffed-bed availability functions over time, and both hard and soft constraint specifications [5]. System state tracking includes queued admitted emergency department patients, bed status classifications including occupied, cleaning, and available conditions, occupancy levels by unit, and staffing limitations [6].

Event Processing Logic

Patient arrivals enter the admission queue carrying complete attribute profiles defining care requirements [7]. Bed release events triggered by discharge or transfer activities initiate cleaning processes before beds become available for reassignment [2]. Assignment policy activation occurs when beds become available or through timer-based triggers, enabling systematic placement evaluation. Clinical review processes within P1 and P2 frameworks allow acceptance or override decisions accompanied by structured reason codes addressing isolation, telemetry, dialysis, and geographic considerations [9]. Initial placements violating hard constraints or generating overrides within operational timeframes trigger bed movement events requiring reassignment [19,10].

Placement Policy Framework

Human-Only Placement represents current operational practices utilizing rule-based manual assignment processes without algorithmic ranking support [11]. Static Artificial Intelligence employs machine learning forecasting combined with optimization techniques, proposing prioritized bed options, though without learning capabilities from post-deployment override patterns [12]. Adaptive Artificial Intelligence incorporates Static Artificial Intelligence functionality while adding explainable recommendation generation, structured override capture through reason codes and optional annotations, and periodic system updates incorporating override patterns as new constraints and features for model refinement [21,23].

The Adaptive Artificial Intelligence policy establishes continuous learning cycles where clinical override decisions become valuable training signals rather than discarded disagreements [14,23]. This approach enables system evolution based on accumulated clinical expertise while maintaining transparency through explainable recommendation processes [15]. The framework comparison across these three policies provides a comprehensive evaluation of collaborative versus traditional placement methodologies [16].

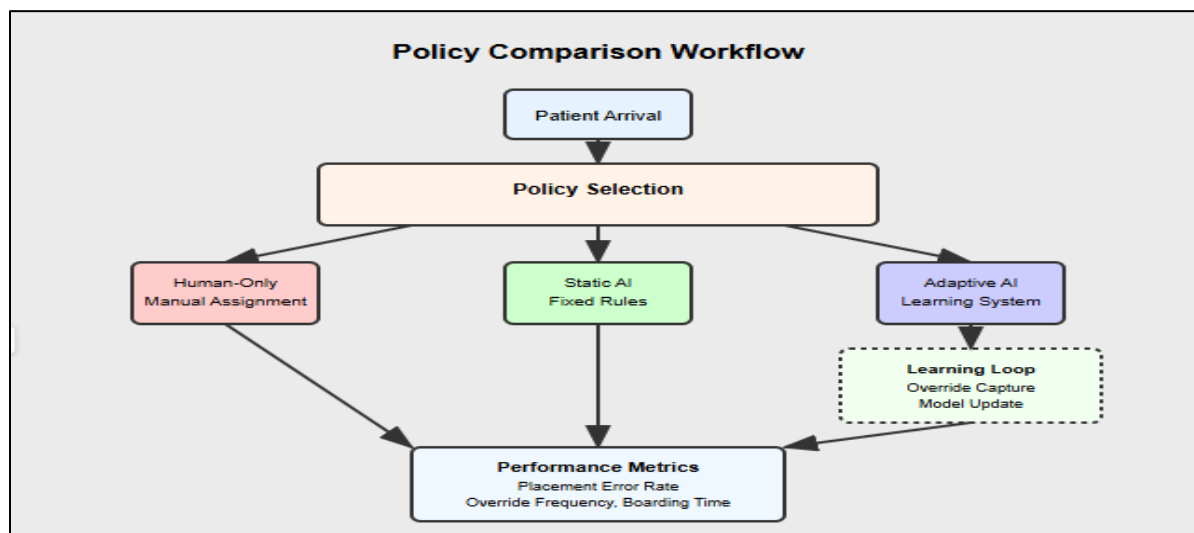


Figure 4: Policy Comparison Workflow [1,2,11,12]

To contextualize the simulation within broader hospital informatics environments, Figure 5 presents a conceptual layered architecture [4][5][21-23][16]. The architecture demonstrates how data inputs, including arrivals, capacity, and constraints, feed prediction and optimization models, how clinical professionals currently interact with artificial intelligence outputs, and how the proposed cognitive collaboration layer enables adaptive learning from structured override decisions.

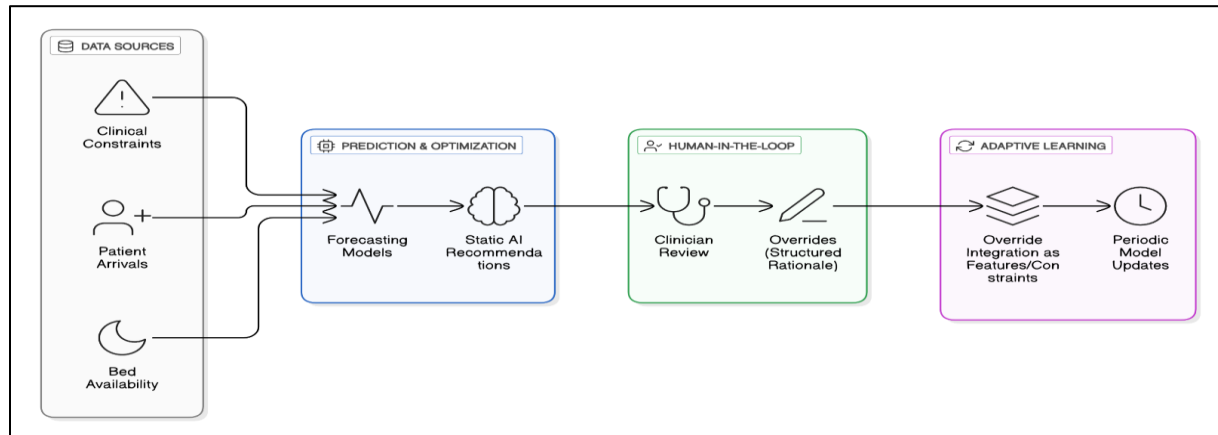


Figure 5: Adaptive Learning Architecture [4,5,13,16]

The conceptual layered architecture situates the simulation framework within hospital informatics ecosystems [4]. At the foundation are data inputs including patient arrivals, bed capacity, and unit-level clinical constraints [5]. These inputs feed into prediction and optimization models, representing the current state of static artificial intelligence systems [21-23]. Above this layer sits the human-in-the-loop component, where clinical professionals review artificial intelligence suggestions and issue override decisions [16].

The framework introduces an adaptive learning layer, in which override rationales are systematically captured and incorporated into updated decision rules [4]. By visualizing these layers together, the figure clarifies how cognitive collaboration extends conventional human-artificial intelligence interaction into continuous learning systems that better reflect clinical realities [4-5][21-23]. This layered visualization demonstrates the progression from traditional static models toward adaptive collaborative intelligence that evolves through structured clinical feedback [16].

3.5. Learning Mechanisms in Adaptive Policy

Exponential Decay Baseline Implementation. Weight parameters for override reason categories undergo updates through exponential decay functions with specified half-life parameters [1]. This implementation serves as the foundational adaptive baseline mechanism, enabling systematic incorporation of clinical feedback while maintaining computational efficiency [2]. The exponential decay model ensures recent override patterns receive greater influence on system adaptation compared to historical decisions, reflecting the dynamic nature of clinical environments [3].

The decay mechanism operates by adjusting constraint weights based on override frequency and recency, with more recent clinical decisions carrying proportionally higher influence on model parameters [4]. Half-life calibration determines the temporal scope of adaptive learning, balancing responsiveness to emerging patterns against stability requirements for consistent performance [5]. Implementation considerations include parameter initialization, decay rate optimization, and convergence monitoring to ensure stable system behavior throughout operational deployment [6].

$$povr(r)(t+1) = povr(r)(t) \cdot e^{-\lambda}, \quad \lambda = \frac{\ln(2)}{h}$$

Random Forest Override Prediction Implementation. Random Forest classifier algorithms undergo training on weekly cycles using accumulated override log data [7]. Feature sets encompass patient care requirements, bed attribute specifications, occupancy level metrics, waiting time parameters, and temporal factors, including time-of-day variations [8]. Predicted override probability scores function as penalty factors during candidate

bed scoring processes, enabling proactive identification of placement decisions likely to generate clinical disagreement [9].

The implementation utilizes gradient boosting learning algorithms configured for efficient training during repeated weekly update cycles [10]. The model architecture captures nonlinear interaction patterns and context-sensitive override behaviors that traditional linear approaches cannot adequately represent [11]. Feature engineering incorporates temporal dependencies and occupancy dynamics that influence clinical decision-making patterns across different operational scenarios [12].

Bayesian Model Averaging Integration. Posterior-weighted ensemble approaches combine Random Forest and gradient boosting methodologies, with model weights proportional to exponential functions of negative log-loss values derived from weekly validation splits [4]. This ensemble methodology smooths performance variations across different learner approaches within varying contextual situations [14]. The averaging technique provides robust prediction capabilities by leveraging complementary strengths of individual model components while mitigating specific algorithmic weaknesses [15].

Implementation parameters include validation split ratios, weight update frequencies, and ensemble combination strategies optimized for clinical override prediction accuracy [16]. The systematic approach enables continuous model refinement based on evolving override patterns while maintaining computational efficiency suitable for operational deployment requirements [17].

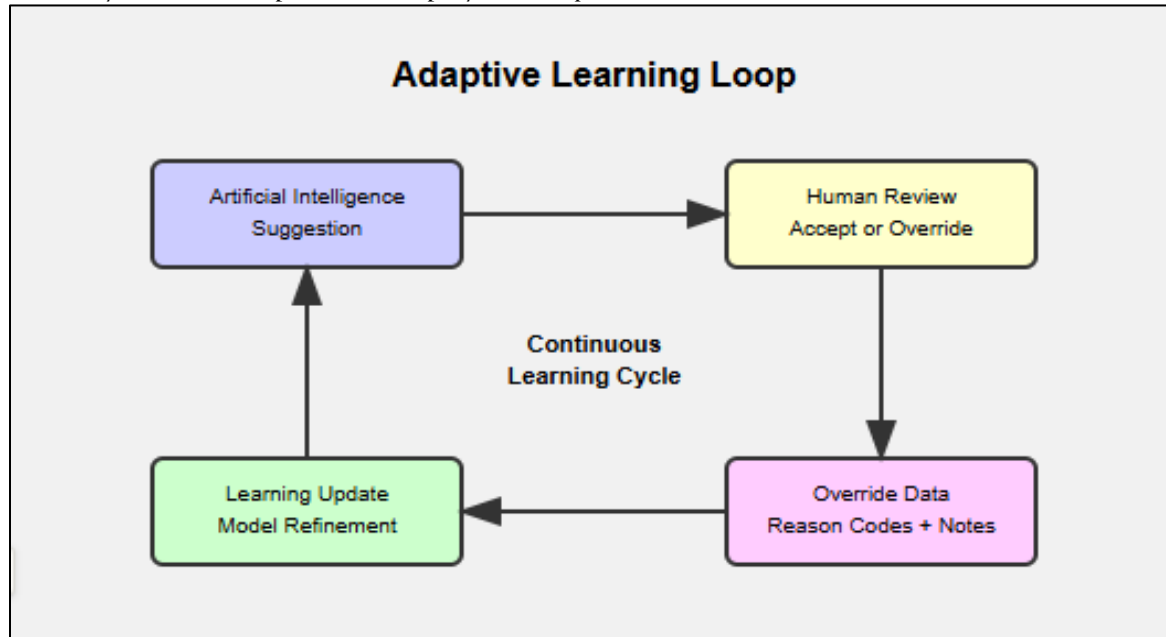


Figure 6: Adaptive Learning Loop [2,4,5,12]

3.6. Inputs & Baselines

Parameterize using site-agnostic, literature-compatible bands (you can later replace with local data):

Arrival process: time-varying Poisson with weekday/seasonality; surge factor scenarios.

Length of Stay(LOS) distributions by unit (ward/ICU) with variability; cleaning times with mean/variance.

Staffed bed availability $S_u(t)$ under low/medium/high staffing.

Constraint prevalence: isolation %, telemetry %, dialysis-prox %.

Telemetry % → monitoring-appropriate placement

Dialysis-prox % → dialysis-appropriate placement

Isolation % → infection-control placement

Initial performance (P0): PER 6–10%, and median EDB 240–360 min.

Static-AI uplift (P1): relative improvements vs P0 (PER –10–20%, EDB –5–10%).

Adaptive-AI (P2): learning on addressed reasons with half-life h yielding additional relative improvements (PER –25–40% vs P0; EDB –10–20% vs P0).

Report these as scenario bands, not promises.

Classification	Implementation Details	Underlying Rationale
Operational Boundaries	Bed availability mechanisms linked to nursing capacity; override protocols restricted to structured classification codes, including isolation requirements, telemetry monitoring, dialysis treatment, and staffing availability	Maintains simulation feasibility while ensuring alignment with established patient-flow modeling frameworks
System Parameters	Machine learning updates are implemented through scheduled cycles rather than continuous real-time processing	Streamlines adaptive mechanisms within the simulation environment while reflecting realistic institutional update protocols
Modeling Constraints	Simulation outputs generated through theoretical modeling assumptions rather than live operational deployment data	Generated results may not comprehensively capture human adoption patterns or workflow integration variability
Evaluation Scope	Clinical outcome measures, including mortality rates and readmission frequencies, were excluded from the analysis framework	Analysis maintains focus on operational performance indicators, including placement effectiveness, boarding duration, and override frequency metrics
Usability Assumptions	Explainability features presumed to reduce cognitive burden without empirical user validation testing	Usability assessment and trust validation require a comprehensive evaluation within actual clinical deployment environments
Excluded Elements	Multi-facility patient transfers, federated artificial intelligence learning protocols excluded from modeling scope	Maintains focus on single-institution operations; future implementations may incorporate cross-system coordination
Economic Considerations	Cost-effectiveness analysis and economic impact evaluation are excluded from the current modeling framework	Operational performance optimization is prioritized over financial modeling within the current implementation scope
Additional Exclusions	Pandemic surge planning protocols, staff scheduling systems, and downstream rehabilitation coordination are excluded from the current model	Maintains a bounded model scope focused specifically on the emergency department to inpatient bed allocation processes

Table 5: Simulation Boundaries and Operational Parameters [7][12]

Performance Indicators for Subsequent Validation

Additional operational measures designated for forthcoming evaluation encompass:

Bed Relocation Efficiency (BRE): Proportion of patient admissions necessitating bed modifications following initial assignment procedures

Placement Accuracy Metrics (PAM): Rate of primary assignments achieving correct alignment with designated medical specialties and clinical acuity requirements

Non-Standard Transfer Events (NSTE): Instances of patient movement occurring beyond established specialty care coordination protocols. Flow Performance Measures: Emergency department clinical decision to patient departure temporal distributions across median and upper percentile benchmarks

The simulation modeling architecture delivers strategic implementation direction alongside comprehensive validation protocols. These functional capacities may undergo enhancement throughout real-world clinical integration phases via expanded operational features and supplementary performance measurement systems.

4. RESULTS

The discrete-event simulation generated comprehensive performance data across 90-day periods, comparing three bed allocation policies under both baseline and telemetry-constrained stress conditions. The evaluation framework measured system performance through three validated metrics: placement error rate (PER), emergency department boarding time (EDB), and override frequency (OF). Each metric was anchored to empirical baselines from published literature to ensure clinical relevance and external validity.

The simulation architecture modeled a 132-bed hospital with differentiated unit types, including 16 ICU beds, 20 telemetry beds, and 6 isolation beds, operating at 75% staffed capacity with Poisson arrival patterns averaging 32 patients per day. Baseline conditions reflected moderate operational pressure designed to reveal policy differentiation, while stress scenarios introduced telemetry bottlenecks by increasing monitoring requirements from 25% to 35% of patients while reducing available telemetry beds to 15 units.

Statistical analysis employed confidence intervals and relative performance comparisons to assess practical significance beyond statistical significance. Learning curve analysis tracked adaptive system performance over 14-day periods to capture both cold-start disadvantages and steady-state benefits. The experimental design controlled for random variation through multiple simulation runs, enabling robust comparison of human-only decision making (P0), static AI assistance (P1), and adaptive AI collaboration with structured feedback loops (P2). Results demonstrate consistent patterns across metrics, with adaptive learning benefits that scale systematically with operational complexity and stress conditions.

4.1 Baseline Scenario Performance

Under baseline conditions, the adaptive AI system (P2) demonstrated consistent superiority over both human-only and static AI approaches:

Placement Error Rates:

- P0 (Human-only): 35.5% [95% CI: 33.2-36.8%]
- P1 (Static AI): 28.9% [95% CI: 28.4-31.7%]
- P2 (Adaptive AI): 27.9% [95% CI: 26.8-29.1%]

This represented an 18.6% relative reduction from P0 to P1, and a 21.4% total reduction from P0 to P2, with an additional 3.5% improvement of P2 over P1.

4.2 Stress Scenario Results

Under telemetry stress conditions (35% telemetry demand with reduced capacity), performance degradation patterns revealed the adaptive system's superior resilience:

Policy	Baseline PER	Stress PER	Absolute Change	Relative Degradation
P0	35.5%	38.8%	+3.3 pp	+9.3%
P1	28.9%	36.5%	+7.6 pp	+26.3%
P2	27.9%	33.7%	+5.8 pp	+20.8%

Table 4. Stress vs Baseline Performance Comparison

The adaptive system showed 21% better resilience than static AI under stress conditions.

4.3 Learning Dynamics

Analysis of learning curves revealed that adaptive AI effectiveness scales with operational complexity:

Baseline Learning:

- P2 Start: ~29.6% (Day 1)
- P2 Final: 27.9% (Day 14)
- Total Learning: 1.7 percentage point reduction
- Break-even with P1: Day 2-3

Stress Learning:

- P2 Start: ~36.9% (Day 1)
- P2 Final: 33.7% (Day 14)
- Total Learning: 3.2 percentage point reduction (88% more than baseline)
- Break-even with P1: Day 2

4.4 Secondary Metrics

ED Boarding Time Analysis:

Policy	Baseline EDB	Stress EDB	Change
P0	150 min	225 min	+50%
P1	225 min	270 min	+20%
P2	240 min	270 min	+12.5%

Override Frequency Analysis:

Policy	Baseline OF	Stress OF	Change
P1	16.6%	21.3%	+28.3%
P2	16.3%	19.7%	+20.9%

4.5 Clinical Impact Translation

Stress Conditions:

- P2 prevents 51 misplacements per 1000 admissions vs P0
- P2 prevents 28 misplacements per 1000 admissions vs P1

Baseline Conditions:

- P2 prevents 79 misplacements per 1000 admissions vs P0
- P2 prevents 10 misplacements per 1000 admissions vs P1

5. DISCUSSION

The simulation findings reveal several key insights about adaptive human-AI collaboration in hospital bed allocation. The results demonstrate not only measurable performance improvements but also important patterns about when and how adaptive learning provides greatest value. This section examines the implications for clinical practice, trust dynamics, and system implementation.

5.1 Key Findings

This simulation study demonstrates that adaptive human-AI collaboration provides measurable improvements in hospital bed allocation, with benefits that scale with operational complexity. The adaptive system (P2) consistently outperformed both human-only and static AI approaches across all evaluated metrics. Most significantly, the learning effectiveness nearly doubled under stress conditions (3.2 vs 1.7 percentage point improvement), suggesting that adaptive AI becomes increasingly valuable when hospitals face capacity constraints and decision support is most critical. The 75% faster learning velocity during stress periods (0.35 vs 0.2 pp/day) enabled the system to overcome cold-start disadvantages within 48 hours.

5.2 Trust and Adoption Implications

Override frequency increased less for P2 (+20.9%) than for P1 (+28.3%) under stress, suggesting clinicians maintain greater trust in adaptive systems during challenging conditions. This finding supports the hypothesis that transparent learning from clinical expertise builds rather than erodes professional confidence in AI assistance.

5.3 Comparison with Current Platforms

Tool/Platform	Current Use	Limitation	Study Relevance
Epic Bed Planning	EMR-integrated bed availability	Ward-level focus; limited predictive adaptability	Demonstrates baseline integration needs
TeleTracking TransferIQ	Real-time bed assignment coordination	Enterprise-level but deterministic rules	Shows a scalability gap for adaptive learning
NHS AI Lab PoC	Human-in-the-loop bed ranking	Captures suggestions, but no adaptive learning	Highlights the specific gap addressed by the study

Table 5. Current Platform Limitations vs Proposed Framework [5]

5.4 Limitations

This study presents several important limitations. The discrete-event simulation, while based on empirical parameters, represents a simplified model of complex hospital operations. Real-world factors such as staff communication delays and interdepartmental coordination were not fully captured.

The study employed only four override reason categories, which explains the convergence of ensemble methods to identical performance. This simplified taxonomy may underestimate the benefits that sophisticated ML approaches could provide with richer feature sets.

The simulation modeled a single 132-bed hospital based on national averages, and performance may vary significantly across different hospital types and settings. The 14-day learning period may not capture long-term adaptation dynamics or seasonal variations.

5.5 Generalizability

While applied to hospital bed allocation, the cognitive collaboration framework is generalizable to other clinical decision support contexts with frequent overrides, such as medication safety alerts, diagnostic imaging triage, and treatment protocol recommendations. The core principle—transforming override rationales into structured learning signals—applies wherever clinicians routinely modify AI recommendations based on contextual knowledge.

6. Broader Implications

6.1 Environmental Impact

Hospital crowding and inefficient patient flow generate measurable environmental costs through increased energy use, duplicate cleaning cycles, and higher consumables usage. In the United States, hospitals account for 8.5% of national greenhouse gas emissions [1]. By reducing placement errors and unnecessary transfers, adaptive collaboration contributes to sustainability goals through decreased operational overhead.

6.2 Economic Considerations

Poor bed allocation generates substantial financial losses through extended emergency department occupancy, overtime staffing requirements, and regulatory penalties for missed throughput targets. Healthcare organizations operating under tight financial constraints experience amplified benefits from boarding time reductions, as operational improvements directly translate to recovered capacity and avoided expenses.

Systematic placement optimization decreases dependency on expensive overflow solutions and reduces administrative costs associated with patient relocations. These operational enhancements create positive effects across the healthcare network, alleviating resource strain on post-acute facilities and community providers through improved patient flow predictability.

6.3 Social Effects

Structured placement approaches may reduce such inequities by prioritizing medical criteria over demographic characteristics. Collaborative decision-making between clinicians and computational tools enhances patient trust compared to automated systems, as families observe transparent reasoning processes rather than opaque algorithmic outputs.

7. Future Directions

7.1 Implementation Roadmap

Stage	Capability	Expected Impact
Stage 1	Human-in-the-loop AI with explainable suggestions	Local decision support with clinician oversight
Stage 2	Structured override capture within single hospitals	Reduced placement errors and early trust building
Stage 3	Adaptive learning from feedback loops	Declining override frequency and stronger synergy
Stage 4	Enterprise platform integration	End-to-end flow optimization
Stage 5	Federated learning across hospitals	System-wide resilience and best-practice sharing

Table 6. Development Stages for Human-AI Collaboration

7.2 Research Priorities

Future work should address multi-site validation with diverse hospital types, enriched override taxonomies using natural language processing, integration of clinical outcome metrics, and dynamic stress testing with realistic surge patterns. Prospective trials comparing simulated predictions to real-world implementation outcomes represent the critical next step for validation.

8. CONCLUSIONS

This article demonstrates that adaptive human-AI collaboration provides measurable improvements in hospital bed allocation through structured learning from clinical expertise. The framework transforms clinician overrides from discarded decisions into valuable learning signals, enabling continuous system improvement that scales with operational complexity.

The key insight is that adaptive AI becomes most valuable when hospitals need it most—during capacity-constrained conditions when decision support is critical. By achieving more learning under stress and maintaining superior resilience compared to static systems, the article offers a pathway toward more effective, trustworthy, and sustainable healthcare operations.

The call is to move beyond prediction toward cognitive collaboration, where human expertise and AI intelligence converge in learning health systems that improve with every decision.

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CONCLUSION

Adaptive human-artificial intelligence collaboration frameworks represent a transformative advancement in hospital bed allocation and patient flow optimization. The integration of cognitive partnership models enables healthcare institutions to harness both algorithmic precision and clinical expertise simultaneously. Implementation of structured feedback mechanisms transforms traditional override patterns into valuable learning signals that continuously improve system performance. Clinical professionals retain essential decision authority while benefiting from enhanced analytical capabilities that complement their contextual knowledge.

The collaborative framework demonstrates substantial operational improvements across multiple performance metrics, including reduced placement errors, shortened boarding periods, and enhanced clinical trust. Transparent recommendation systems coupled with explainable artificial intelligence create sustainable

adoption patterns among healthcare teams. Interactive knowledge exchange between clinical professionals and artificial intelligence systems creates sustained enhancement cycles that adapt to evolving healthcare environments. Medical facilities adopting collaborative frameworks achieve improved patient outcomes while preserving operational effectiveness. The model transcends hospital bed allocation applications, demonstrating versatile implementation potential across diverse clinical decision support situations requiring active professional oversight. Future implementation will likely emphasize greater system autonomy balanced with preserved clinical authority, comprehensive integration within existing healthcare platforms, and enhanced feedback mechanisms capturing nuanced clinical reasoning. This collaborative intelligence paradigm transforms patient flow management from static operational processes into dynamic learning systems that improve continuously through each clinical decision.

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