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Artificial Intelligence Framework for Real-Time Prioritization of Inpatient Transport Requests Using Patient Acuity, Destination Urgency, Transporter Availability, Elevator Congestion, and Unit-Level Transfer Demand

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Abstract

Inpatient transport is a critical but often under-recognized component of hospital operations. Delays in moving patients between wards, diagnostic areas, procedural suites, and discharge locations can disrupt clinical schedules, prolong waiting, and expose vulnerable patients to avoidable risk. Many hospital transport workflows still rely on first-in-first-out queues, dispatcher judgment, or simple proximity-based assignment. These approaches may overlook patient acuity, destination urgency, transporter workload, elevator congestion, and anticipated surges in unit-level demand. This article proposes an AI systems framework that continuously assigns a dynamic priority score to each inpatient transport request. The framework integrates patient acuity, destination urgency, transporter availability, elevator congestion, and forecasted unit-level transfer demand into a real-time dispatch logic. The framework includes a patient acuity stratification module, destination urgency classifier, transporter tracking layer, elevator congestion model, unit-level demand forecaster, and real-time prioritization engine. These components would operate as an integrated decision-support system rather than as isolated scheduling tools. The framework could support safer and more responsive transport decisions by aligning dispatch priority with both clinical risk and operational constraints. It would be expected to improve coordination among transporters, nursing units, procedural areas, and hospital command centers. A real-time AI transport prioritization framework offers a pathway toward more intelligent inpatient logistics. Its value should be evaluated through phased implementation, transparent governance, and careful assessment of clinical and operational consequences.

Keywords Artificial intelligence, Patient acuity, Inpatient transport, Hospital logistics, Real-time prioritization, Transporter dispatch

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Introduction

Inpatient transport connects core hospital functions by moving patients among wards, intensive care units, diagnostic imaging areas, operating rooms, catheterisation laboratories, procedural suites, and discharge destinations. When transport is delayed, downstream clinical workflows can be disrupted through late surgical starts, missed imaging slots, extended emergency department boarding, and delayed bed turnover [1-3]. Transport also creates a period of clinical

vulnerability for unstable patients because monitoring, staffing, and equipment conditions may change once the patient leaves the unit [4, 5]. For this reason, inpatient transport should be understood as both a logistics function and a patient-safety process rather than as a purely ancillary service [6, 7].

Current transport dispatch models are often constrained by static rules, manual triage, and incomplete visibility into real-time bottlenecks. Mixed-integer planning, process analysis, and decision-support studies show that transport systems can be formalised operationally, yet many practical workflows still rely on first-come-first-served ordering or dispatcher judgment rather than dynamic prioritization [1, 8, 9]. Such models may not adequately integrate clinical urgency, destination time sensitivity, staff availability, or infrastructure constraints such as elevators and corridors [10, 11]. The resulting mismatch between request priority and system state can create avoidable waiting for urgent transports while lower-risk movements consume scarce transporter capacity [2, 12].

Several enabling technologies now make real-time AI-based transport prioritization more feasible. Real-time location systems, mobile task-management tools, hospital command centers, EHR-derived acuity indicators, admission-discharge-transfer feeds, and elevator control data can collectively describe both patient need and operational capacity [2, 10, 12]. Forecasting work on admissions, bed demand, emergency department flow, and hospital occupancy suggests that near-term demand signals can be incorporated into operational planning before congestion becomes visible at the queue level [13-15]. However, these streams are rarely fused into a single transport-specific prioritization framework that can continuously re-rank requests and recommend assignments [16, 17].

This AIF article proposes a real-time AI framework for prioritizing inpatient transport requests by synthesising clinical and operational data streams. The framework conceptualises each transport request as a dynamic object whose priority changes with patient acuity, destination urgency, transporter state, elevator congestion, and unit-level demand forecasts. Rather than replacing dispatcher oversight, the system would provide explainable priority recommendations and assignment suggestions within existing transport command workflows. The central thesis is that inpatient transport should move from reactive queue management toward clinically informed, continuously updated logistics intelligence.

Background

The hospital transport ecosystem

The hospital transport ecosystem includes porters or transporters, transport nurses, unit nurses, dispatchers, procedural departments, bed-management teams, and command center personnel. Each transport request must coordinate patient readiness, escort requirements, destination availability, equipment needs, infection-control constraints, and route feasibility [8, 9]. Process mining and transport planning research indicates that transport work is shaped by both local request patterns and system-wide bottlenecks, making isolated task assignment insufficient for complex hospitals [1, 8]. A real-time prioritization framework should therefore treat each request as part of a wider logistics network rather than as an independent work order [2, 3].

Patient acuity and clinical risk during transport

Patient acuity is central to inpatient transport because critically ill, ventilated, sedated, monitored, or haemodynamically unstable patients may experience deterioration during movement. Studies of intrahospital transport have documented adverse events and safety vulnerabilities among critically ill patients, particularly when equipment, monitoring, staffing, or handoff processes are inadequate [4-6]. Quality-improvement and emergency transport studies further suggest that systematic risk identification, structured checklists, and transport-specific safety processes are important for reducing preventable harm [7, 18, 19]. An AI prioritization framework should therefore elevate requests in which transport delay or prolonged out-of-unit exposure could increase clinical risk [20, 21].

Destination urgency: OR, radiology, and timed appointments

Destination urgency reflects the operational and clinical consequences of arriving late to a receiving area. Transport to operating rooms, radiology, catheterisation laboratories, urgent diagnostic imaging, emergency transfers, and timed procedures may carry higher urgency than routine discharges or non-time-sensitive movements [2, 3]. Emergency department triage and admission-prediction studies show that clinical context can be used to anticipate downstream care pathways, which supports the idea that destination type and scheduled time should influence transport priority [22-24]. A transport framework should distinguish routine movement from transports tied to time-sensitive diagnostic or therapeutic windows, while allowing clinical override when risk is not captured by the schedule alone [25, 26].

Transporter workforce and real-time location systems

Transporter workforce management requires real-time awareness of who is idle, assigned, en route, carrying a patient, delayed, unavailable, or nearing the end of a shift. RTLS-enabled porter management has shown how indoor positioning can support trace analysis, task visibility, and operational monitoring within hospital transport services [10]. Broader logistics and command-center studies indicate that assignment decisions should account not only for proximity but also workload balance, queue state, future demand, and downstream congestion [2, 3, 12]. In an AI framework, transporter availability should be represented as a state vector that updates continuously rather than as a static list of staff names [1, 17].

Elevator congestion and infrastructure bottlenecks

Elevator congestion is a distinctive bottleneck in inpatient transport because vertical movement can dominate route time in multi-floor hospitals. Elevator dispatching and modelling studies show that uncertain passenger arrivals, destination control, and power or usage patterns can be represented analytically, which makes elevator delay suitable for integration into logistics decision-support [11, 27]. Transport planning should therefore consider not only the horizontal distance between transporter and patient but also vertical route feasibility, elevator queues, peak demand, and service interruptions [1, 9]. A real-time priority system could incorporate an elevator congestion index so that assignment and routing decisions reflect the actual infrastructure state rather than a simplified map distance [10, 11].

Framework Overview

High-level architecture

The proposed framework would ingest real-time data from the EHR, transport request platform, RTLS layer, admission-discharge-transfer system, procedure scheduling systems, and infrastructure sensors. EHR data would inform acuity and special handling needs, request data would describe destination and timing, RTLS data would locate transporters and infer task state, and ADT feeds would describe unit census and bed movement pressure [10, 14, 28]. Elevator status and congestion signals would provide route-level constraints, while command-center integration would present priority recommendations to dispatchers within existing operational workflows [2, 3, 11]. The priority engine would then compute and continuously update a composite score for each pending request [17, 29].

Figure 1 illustrates the proposed real-time AI framework for inpatient transport prioritization, showing how clinical, operational, workforce, infrastructure, and demand signals are converted into explainable dispatch recommendations under human oversight.

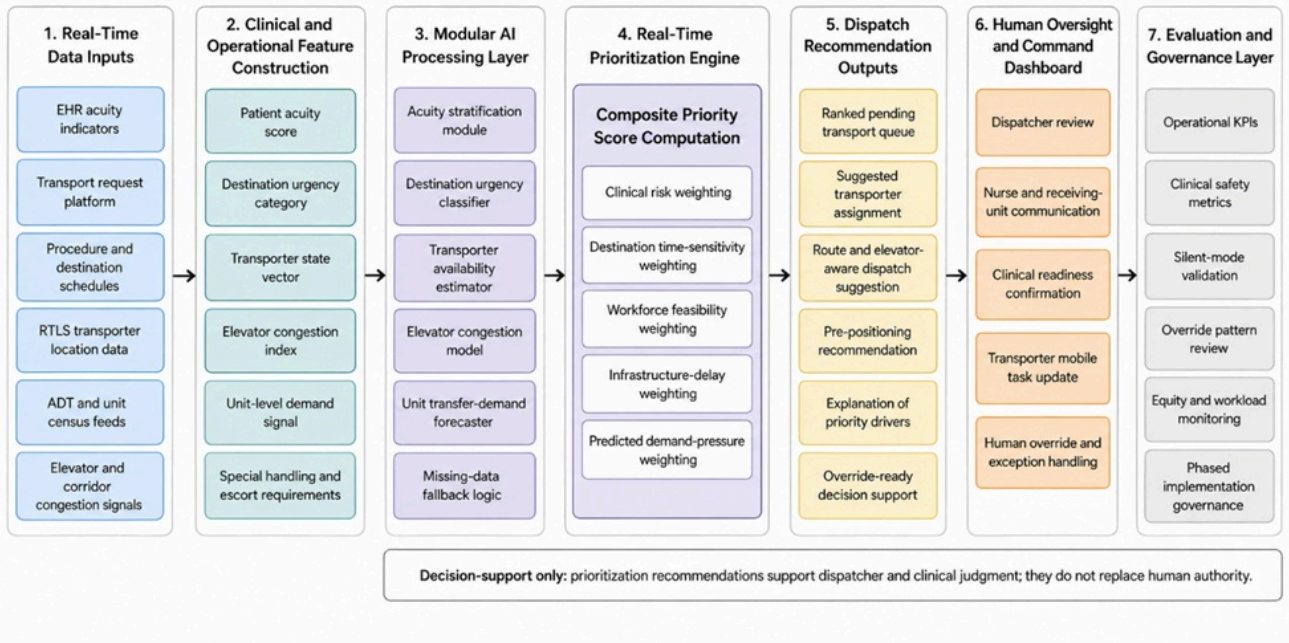


Figure 1. Real-Time AI Framework for Prioritizing Inpatient Transport Requests

Core inputs and outputs

The core inputs would include a patient acuity score, destination urgency category, transporter status vector, elevator congestion index, and predicted unit-level demand signal. These inputs would combine clinical data, operational data, and infrastructure data so that priority reflects both patient risk and system capacity [12-14]. The main output would be a dynamically updated priority score for every pending transport request, accompanied by a suggested transporter assignment and a concise explanation of the factors driving the recommendation [1, 10]. This output should be designed to support dispatcher judgment rather than to create an opaque automated queue [2, 3].

Table 1 presents the conceptual logic through which clinical, operational, workforce, infrastructure, and demand signals are transformed into explainable inpatient transport prioritization decisions.

Table 1. Conceptual Logic Linking Transport Prioritization Inputs to AI Processing Modules and Dispatch Decisions

Prioritization Domain	Core Data Elements	AI/Analytical Function	Decision-Relevant Interpretation	Risk if Omitted
Patient acuity	Vital instability, oxygen/ventilation status, monitoring needs, sedation, isolation, escort requirements	Acuity stratification	Identifies transports where delay or prolonged movement may increase clinical risk	Clinically vulnerable patients may remain buried in routine queues
Destination urgency	OR slot, imaging appointment, catheterisation lab timing, urgent transfer, receiving-area readiness	Destination urgency classification	Distinguishes time-sensitive transports from routine movements	Procedure delays, missed diagnostic windows, downstream schedule disruption
Transporter availability	RTLS location, task state, mobile timestamps, workload,	Transporter state estimation	Determines feasible staff capacity beyond	Nearest-worker assignment may

	shift status		simple proximity	overload staff or select unavailable transporters
Elevator congestion	Elevator logs, vertical route demand, waiting time, service interruption, corridor congestion	Infrastructure-delay modelling	Estimates actual route feasibility rather than map distance alone	Assignments may appear efficient but fail because of vertical bottlenecks
Unit-level transfer demand	ADT feeds, census, pending admissions, discharge orders, procedure schedule, ED boarding	Near-term demand forecasting	Anticipates transport surges before queues become visible	Dispatch remains reactive and poorly positioned for predictable demand waves
Priority recommendation	Combined clinical, operational, workforce, infrastructure, and demand signals	Composite priority scoring	Produces ranked queue and assignment suggestions with explainable drivers	Dispatch remains dependent on FIFO rules or opaque manual judgment
Human oversight	Dispatcher review, nurse communication, clinical override, exception documentation	Sociotechnical governance	Preserves accountability and local clinical judgment	Algorithmic dispatch may become unsafe, opaque, or resisted by staff

Design principles

The framework should be real-time, low-latency, clinically informed, resilient to missing sensor data, and compatible with existing dispatch software. It should allow degradation to rule-based or manually verified logic when RTLS, elevator, or EHR feeds are unavailable, because hospital data streams may be incomplete or intermittently delayed [2, 10, 12]. It should also support transparent prioritization so that dispatchers, nurses, and transporters can understand why one transport is ranked above another [3, 19]. Finally, the system should be evaluated as a sociotechnical intervention embedded in hospital operations, not merely as a predictive model [16, 17].

Patient Acuity and Destination Urgency Modelling

Extracting acuity from EHR and monitoring data

The patient acuity module would use EHR and monitoring indicators such as vital-sign instability, oxygen or ventilation status, vasopressor requirements, continuous monitoring needs, isolation flags, sedation status, and need for specialized escort. Critical-care machine learning research shows that clinical deterioration and circulatory instability can be represented dynamically, supporting the conceptual use of continuously updated acuity signals in transport prioritization [20, 21]. Sepsis treatment and emergency triage studies further illustrate how clinical state and care trajectory can inform time-sensitive operational decisions [22, 24, 26]. In this framework, acuity would not be used to diagnose or treat the patient but to determine whether delayed or prolonged transport could elevate operational and safety risk [4, 6].

Classifying destination urgency

The destination urgency classifier would group transports according to scheduled procedure time, receiving-area sensitivity, clinical priority, and transport purpose. Requests for operating rooms, radiology appointments, catheterisation laboratories, urgent imaging, emergency transfers, and high-priority consultations would be treated differently from routine returns, discharges, or non-urgent bed moves [2, 3]. Emergency department admission-prediction and patient-flow

studies suggest that anticipated care pathways and disposition risk can guide operational planning, which supports destination-aware prioritization in transport dispatch [23-25]. The classifier should remain configurable so that each hospital can encode local procedural workflows without hard-coding unsafe or overly rigid priority rules [1, 9].

Acuity-urgency interaction and priority weighting

Acuity and destination urgency should interact rather than operate as separate additive labels. For example, a high-acuity patient requiring time-sensitive imaging should be escalated above a stable patient with a routine destination, even when the stable patient requested transport earlier [4, 5]. Conversely, a low-acuity patient with a fixed procedural slot may still warrant prioritization if late arrival would disrupt a scarce operating room or imaging resource [2, 3]. The weighting layer should therefore combine clinical risk and operational time sensitivity into a transparent priority logic that can be reviewed, adjusted, and governed by clinical and logistics leaders [17, 19].

Transporter Availability and Elevator Congestion Detection

Real-time transporter tracking and state estimation

Real-time transporter tracking would use RTLS, mobile task timestamps, and dispatch-system events to infer whether a transporter is idle, assigned, moving to pickup, transporting a patient, returning equipment, delayed, or unavailable. Indoor porter-management research demonstrates that location traces can be analysed to understand movement patterns and support operational visibility, although raw location data may require interpretation before it becomes useful for dispatch decisions [10]. Bayesian filtering or similar smoothing logic could reduce the effect of noisy location signals and prevent unnecessary reassignments based on transient positioning errors [10, 17]. The resulting transporter state estimate should feed the priority engine as a dynamic capacity signal rather than as a simple nearest-worker rule [1, 2].

Elevator and corridor congestion modelling

The elevator congestion model would estimate current and anticipated vertical-transport delay using elevator control logs, sensor signals, historical traffic patterns, and observed transporter movement. Elevator dispatching research on uncertain passenger arrivals and destination-control systems provides a conceptual basis for representing elevator delay as a dynamic operational constraint rather than as a fixed travel-time assumption [11]. High-resolution modelling of elevator usage further indicates that elevator activity can be measured and represented in ways that may support operational forecasting in complex buildings [27]. By integrating elevator and corridor congestion into route planning, the framework could avoid assigning a nominally close transporter whose path is likely to be delayed by infrastructure bottlenecks [1, 9].

Matching transporter to task in a dynamic environment

In a dynamic hospital environment, matching a transporter to a task should consider the combined clinical risk of all waiting requests rather than the closest available worker alone. Optimization and patient-flow research suggests that operational decisions can be improved when assignment logic accounts for queue state, future demand, and system constraints instead of treating each request independently [1, 28, 29]. The proposed framework would therefore evaluate candidate assignments by considering patient acuity, destination urgency, transporter state, elevator congestion, and predicted demand pressure at origin and destination units [11, 13, 14]. This approach could support workload balancing while preserving dispatcher oversight for exceptions, handoff concerns, and clinical judgment [2, 3].

Unit-Level Transfer Demand Forecasting

Historical patterns of transport request volume

Unit-level transfer demand forecasting would begin by characterising recurring transport request patterns by origin unit, destination type, weekday, shift period, procedure schedule, admission pressure, and discharge workflow. Forecasting studies in emergency department arrivals, occupancy, and hospital flow show that temporal demand signals can support anticipatory operational planning rather than purely reactive queue management [29-31]. Deep learning and patient-flow modelling also suggest that future movement pressure can be represented as a near-term operational signal, although this AIF framework would use such methods conceptually rather than reporting model performance [17, 32]. For inpatient transport, these patterns would help identify predictable demand waves such as morning imaging movements, post-procedure returns, bed transfers, and discharge-related escorts [14, 15].

Predictive signals for near-term demand

Near-term demand signals would include scheduled procedures, imaging appointments, pending admissions, discharge orders, bed requests, emergency department boarding pressure, ICU transfers, and ward-level census changes. Bed demand and admission forecasting studies indicate that operational systems can use hospital data streams to anticipate future capacity needs before a queue becomes visible [13-15]. Hospital decision-support and capacity-planning work further supports the use of integrated forecasting to guide staffing, bed management, and logistics decisions across interconnected services [33, 34]. In the proposed framework, these signals would not determine transport priority alone but would alert the system to likely surges that should shape pre-positioning and assignment recommendations [17, 28].

Integrating demand forecast into priority scores

The demand forecast would enter the priority engine as a contextual modifier that identifies units likely to generate additional requests or experience downstream congestion. When a ward, ICU, emergency department, or procedural area is expected to create a surge of transport demand, the system could suggest positioning idle transporters closer to that area while preserving capacity for urgent requests elsewhere [13, 29, 32]. Inventory and health-care logistics research shows that prescriptive analytics can connect forecasts with operational decisions, which supports the conceptual integration of demand prediction and dispatch recommendation [35]. This integration should remain transparent so that dispatchers can distinguish between transports prioritized because of immediate patient risk and transports influenced by anticipated system pressure [2, 3].

Real-Time Prioritization Engine

Multi-criteria priority score computation

The real-time prioritization engine would compute an actionable score by combining patient acuity, destination urgency, transporter availability, elevator congestion, and unit-level transfer demand. The scoring function could be rule-weighted, optimization-supported, or learned from historical workflow patterns, but it should remain interpretable enough for clinical and operational governance [1, 17, 28]. Patient acuity and destination urgency would represent clinical and procedural risk, while transporter state, elevator congestion, and demand forecasts would represent operational feasibility and near-term system pressure [10, 11, 14]. The score would therefore function as a decision-support signal rather than as an automatic command, allowing dispatchers to override recommendations when local knowledge or safety concerns require it [2, 19].

Dynamic re-prioritisation and transporter re-routing

Dynamic re-prioritisation would occur whenever a new request arrives, a patient's acuity changes, a destination time window shifts, a transporter becomes unavailable, or an elevator bottleneck emerges. Patient-flow and emergency department forecasting studies support the idea that hospital operations are continuously changing systems, requiring prioritization logic that can update as new information becomes available [29-31]. The framework could re-rank pending tasks and suggest re-routing when doing so would be expected to reduce aggregate clinical risk or protect time-sensitive

destinations [1, 9, 32]. Because frequent reassignments can create confusion, the system should include stability rules that avoid unnecessary changes unless the expected operational or clinical benefit is meaningful [2, 3].

Clinical Integration and Transport Command Dashboard

Transport dispatcher dashboard

The transport dispatcher dashboard would present pending requests ordered by priority, transporter locations, task states, congested zones, destination deadlines, and short explanations for each recommendation. Command-center research shows that hospital-wide operational visibility can support coordinated patient-flow management when data streams are converted into actionable displays rather than isolated metrics [2, 3, 12]. The dashboard should therefore emphasise interpretability, showing whether a request is elevated because of patient acuity, destination urgency, transporter scarcity, elevator congestion, or predicted unit demand [10, 11, 14]. One-click dispatch and re-route functions could support efficient response, but final authority should remain with trained dispatchers and clinical teams [2, 19].

Clinical-transporter communication and safety

Clinical integration would require communication between transporters, unit nurses, receiving departments, and dispatchers before, during, and after movement. The framework could connect with nurse call systems, EHR handoff fields, mobile transporter applications, and incident-reporting workflows so that arrival notifications, escort requirements, isolation precautions, and equipment needs are visible at the point of action [4, 10, 19]. Evidence on adverse events during intrahospital transport reinforces the need for structured preparation, monitoring, and post-transport documentation, especially for critically ill or unstable patients [5-7, 18]. The system should therefore treat communication and safety checks as part of prioritization rather than as separate downstream administrative tasks [3, 12].

Evaluation strategy

Table 2 provides an implementation-focused evaluation matrix for assessing whether the proposed AI transport prioritization framework improves operational responsiveness while preserving clinical safety, transparency, and human oversight.

Table 2. Evaluation Matrix for Safe Implementation of the Real-Time AI Inpatient Transport Prioritization Framework

Evaluation Dimension	Candidate Metrics	Evaluation Stage	Interpretation for Framework Safety and Utility	Governance Use
Queue responsiveness	Median response time, tail response time, queue aging, urgent-request waiting time	Simulation and silent mode	Tests whether prioritization reduces clinically meaningful waiting	Determines whether AI ranking improves over FIFO/proximity rules
Time-sensitive destination performance	On-time arrival for OR, radiology, catheterisation lab, urgent imaging, procedural suites	Silent mode and phased activation	Assesses whether the framework protects scarce scheduled resources	Guides destination-specific weighting adjustments
Transporter workload balance	Utilisation, idle time, reassignment frequency, workload concentration, end-of-shift burden	Simulation and live pilot	Detects whether AI dispatch improves efficiency without unfair burden	Supports staff-trust and workload-equity review

Infrastructure-aware routing	Elevator delay, route completion time, congestion-related reassignment, vertical transport delay	Simulation and live pilot	Evaluates whether elevator and route signals improve assignment realism	Validates inclusion of infrastructure data in priority scoring
Clinical safety	Adverse events during transport, escalation events, incomplete handoffs, equipment-readiness failures	Silent mode, pilot, and post-deployment monitoring	Ensures operational gains do not compromise patient safety	Triggers safety review and model recalibration
Human override behavior	Override rate, override rationale, disagreement by unit/destination, recurring exception types	Silent mode and live pilot	Reveals whether recommendations align with real workflow judgment	Supports redesign of rules, explanations, and dashboard displays
Interpretability and trust	Explanation completeness, dispatcher understanding, nurse acceptance, transporter feedback	Usability testing and phased activation	Determines whether staff can understand and act on recommendations	Guides interface design and training
Implementation resilience	Missing-feed frequency, fallback activation, latency, downtime, delayed RTLS/elevator data	Technical validation and live monitoring	Tests whether the framework remains usable under imperfect data conditions	Defines safe fallback and manual-control procedures

Operational key performance indicators

Operational evaluation should examine whether the framework improves the logic, transparency, and responsiveness of transport dispatch without claiming benefits before empirical testing. Candidate indicators could include transport response time, tail response time, on-time arrival for time-sensitive destinations, transporter utilisation, reassignment frequency, queue aging, and dispatcher override patterns [1, 8, 9]. Patient-flow, forecasting, and hospital decision-support studies suggest that evaluation should connect queue behaviour with downstream capacity effects rather than measuring isolated task completion alone [29, 30, 33]. These indicators should be assessed against baseline workflows through simulation or silent-mode deployment before any live dispatch changes are implemented [12, 17].

Clinical safety metrics

Clinical safety evaluation should consider adverse events during transport, escalation events, delayed urgent procedures, incomplete handoffs, equipment-readiness issues, and patient or staff experience. Intrahospital transport studies show that critically ill patient movement can be associated with adverse events and safety vulnerabilities, making clinical monitoring essential for any AI-enabled prioritization system [4-7]. Emergency transport and failure-mode analyses further indicate that structured risk review can identify preventable hazards and guide safer workflow design [18, 19]. The framework should therefore be evaluated not only for operational efficiency but also for whether prioritization decisions align with patient safety, clinical readiness, and receiving-area capacity [20, 21].

Simulation and prospective evaluation

Evaluation should begin with discrete-event simulation or other modelling approaches using historical workflow patterns to compare AI-guided prioritization logic with existing dispatch rules in a controlled environment. Simulation and hospital decision-support research provide a basis for testing how scheduling, queueing, and capacity assumptions interact before

exposing patients and staff to live system changes [1, 9, 33]. A prospective silent-mode evaluation could then display recommendations to observers while preserving existing dispatch operations, allowing researchers to examine agreement, override rationale, safety concerns, and workflow fit without altering care delivery [2, 3, 12]. Only after governance review, staff training, and safety monitoring should the framework be considered for phased activation [16, 17, 34].

Limitations

Data infrastructure and integration gaps

The framework depends on data infrastructure that may not be available in all hospitals, including RTLS coverage, reliable EHR feeds, mobile task timestamps, elevator status data, procedure scheduling integration, and near-real-time ADT information. RTLS studies show the promise of location-aware transport management, but sensor coverage, signal noise, workflow compliance, and local building design can limit the completeness of operational visibility [10]. Forecasting and bed-demand studies also depend on timely, accurate source data, which may be difficult to harmonise across wards, procedural areas, and command-center systems [14, 15, 34]. Hospitals without mature digital infrastructure may need a staged implementation that begins with simpler rule-based prioritization and gradually incorporates richer real-time signals [2, 3].

Resistance to algorithmic dispatch

Algorithmic dispatch may face resistance from transporters, dispatchers, nurses, and clinicians if recommendations appear opaque, disruptive, or insensitive to local workflow realities. Command-center and safety literature suggests that operational technology must be embedded in sociotechnical routines, with attention to communication, accountability, and trust rather than dashboard deployment alone [2, 12, 19]. Transporters may also worry that tracking systems are being used for surveillance instead of workload support, making governance, transparency, and participatory design essential [8, 9]. The framework should therefore provide explanations, preserve human override, collect feedback, and treat disagreement as a source of system learning rather than as user noncompliance [3, 17].

Conclusion

This article proposed an AI framework for real-time prioritization of inpatient transport requests. The framework integrates patient acuity, destination urgency, transporter availability, elevator congestion, and unit-level transfer demand into a dynamic decision-support architecture for hospital transport operations. Its purpose is not to automate clinical judgment but to help dispatchers and care teams align transport priority with patient risk and operational constraints.

The framework's main strength is its fusion of clinical and logistical intelligence. By combining acuity signals, procedure time sensitivity, real-time transporter state, infrastructure congestion, and demand forecasts, the system could support more responsive prioritization than first-come-first-served or proximity-only dispatch. Its command-center orientation also makes it suitable for integration into broader patient-flow and capacity-management workflows.

Important challenges remain before such a framework can be implemented safely. Hospitals differ in sensor infrastructure, EHR integration, elevator data availability, staffing models, and transporter workflows. Human factors are equally important because dispatchers, transporters, and clinical teams must trust the system, understand its recommendations, and retain authority to override it when patient safety or local context requires.

Future work should pursue phased implementation pilots, beginning with simulation and silent-mode evaluation before live deployment. Hospitals and researchers should also collaborate on benchmark transport datasets that capture acuity, destination urgency, transporter state, infrastructure constraints, and unit-level demand in a privacy-preserving format.

Such work would support the development of intelligent, transparent, and clinically grounded transport dispatch systems across complex hospital environments.

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