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Artificial Intelligence Framework for Predicting Medical Equipment Utilization Using Real-Time Location System Data, Procedure Schedules, Maintenance Logs, Unit-Level Demand, and Device Availability Records

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Abstract

Medical equipment shortages and surpluses often coexist in hospitals because utilization is observed after demand has already emerged rather than predicted in advance. Expensive mobile assets may sit idle in low-demand areas while clinicians search for pumps, monitors, beds, ventilators, or imaging-related devices in high-demand units. Current equipment management often depends on manual counts, static par levels, delayed inventory review, and reactive dispatching. These practices do not fully integrate forward-looking signals already present in procedure schedules, unit demand projections, maintenance logs, and device availability records. This article proposes an artificial intelligence framework that ingests real-time location system data, procedure schedules, maintenance logs, unit-level demand forecasts, and device availability records. The framework is designed to generate continuous predictions of equipment utilization and impending shortages across hospital units. The framework includes a real-time location ingestion module, a procedure-schedule demand mapper, a maintenance downtime predictor, a unit-level demand forecaster, a multi-source fusion engine, and an operational decision-support dashboard. These components would convert fragmented hospital data streams into coordinated predictions for equipment planning. The framework would shift equipment management from reactive searching toward proactive allocation. It would be expected to reduce avoidable idle time, improve visibility of available equipment pools, and support earlier decisions about staging, redistribution, maintenance rescheduling, or rental planning. An AI-enabled equipment utilization framework offers a pathway toward a data-driven and anticipatory medical equipment supply chain. Such a framework could help hospitals coordinate scarce assets more effectively in complex, high-pressure clinical environments.

Keywords Artificial intelligence, Predictive analytics, Medical equipment utilization, Real-time location systems, Hospital asset management, Maintenance forecasting

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Introduction

Medical equipment unavailability creates clinical and operational friction when staff know that devices exist somewhere in the hospital but cannot access them when care is needed. Real-time location system studies show that mobile assets and staff move through complex clinical spaces in ways that are difficult to capture through manual counts alone [1, 2]. This

limited visibility contributes to a familiar paradox: some units experience shortages while other areas retain idle or informally hoarded devices. A framework for predicting medical equipment utilization should therefore address not only inventory quantity, but also the time, location, and practical availability of each device type.

Hospitals already collect operational data that could help predict future equipment demand. RTLS platforms can identify where tagged assets are located, while procedure schedules provide advance notice of operating room, endoscopy, imaging, and procedural activity [3, 4]. Maintenance records add another layer by indicating when devices may be removed from circulation for planned or unplanned service [5]. Unit-level demand forecasts, especially those based on census and bed-pressure indicators, can further signal where equipment need is likely to rise before shortages are reported [6, 7].

AI methods are increasingly used to forecast hospital demand, predict operating room case timing, estimate bed occupancy, and support maintenance planning. Bed-demand models demonstrate that census and admission patterns can be transformed into operational forecasts [8, 9]. Procedure-duration prediction studies show that scheduled case characteristics can inform the timing of resource needs in procedural areas [10, 11]. Predictive maintenance research similarly suggests that device history and service records can be used to anticipate future availability constraints rather than simply document past failures [12, 13].

This article proposes an Artificial Intelligence Framework for predicting medical equipment utilization through the integration of RTLS data, procedure schedules, maintenance logs, unit-level demand forecasts, and device availability records. The framework is conceptual and does not report experimental results, dataset sizes, training procedures, or performance metrics. Instead, it explains how existing operational data streams could be fused to predict utilization pressure across device types and hospital locations. The framework builds on evidence that real-time visibility, demand forecasting, surgical scheduling analytics, and centralized operational dashboards can each support hospital resource coordination when aligned with clinical workflows.

Background

Medical equipment management in hospitals

Medical equipment management in hospitals is complicated by asset mobility, uneven demand, local workarounds, and uncertainty about whether devices are clean, functional, in use, or parked. RTLS feasibility work has shown that asset-tracking systems can improve visibility, but visibility alone does not necessarily predict where equipment will be needed next [1]. Manual counts and static par levels may therefore coexist with emergency rentals, corridor storage, and equipment hoarding. Centralized operational management models suggest that resource coordination improves when distributed information is represented in a shared decision environment rather than scattered across units and departments [14, 15].

Real-time location systems for asset tracking

RTLS technologies such as radio-frequency identification, Bluetooth Low Energy, Wi-Fi-based tracking, and ultra-wideband systems can generate repeated observations of device location and movement. Reviews of healthcare RTLS applications show that these systems have been used for asset tracking, workflow analysis, staff-location awareness, and operational monitoring [3]. Studies of provider location and contextual computing further indicate that location data must be interpreted in relation to clinical activity rather than treated as simple coordinates [2, 16]. For equipment utilization prediction, the important step is to translate noisy location signals into meaningful operational states such as idle, in use, in transit, staged, unavailable, or under maintenance.

Procedure schedules and demand signal

Procedure schedules are valuable demand signals because many scheduled cases imply predictable equipment needs before patients arrive in procedural areas. Operating room case-duration studies show that features such as procedure type, specialty, timing, and historical case patterns can support predictions about resource timing [4, 10]. Similar logic can be extended from case-duration prediction to equipment requirement mapping, where scheduled procedures are associated with expected device categories and staging needs. Surgical and procedural schedules would therefore help the framework anticipate peaks in demand for pumps, monitors, beds, imaging-related devices, and specialty equipment [11, 17].

Maintenance logs and equipment downtime

Maintenance logs provide information about device reliability, preventive maintenance, repair history, downtime, and recurring failure patterns. Predictive maintenance research in healthcare indicates that medical equipment service data can support earlier identification of devices at risk of becoming unavailable [5, 12]. Strategic maintenance models further show that equipment prioritization and failure analysis can be incorporated into broader maintenance management decisions [13, 18]. In a utilization framework, these records would reduce the effective available pool when devices are scheduled for service or likely to be removed from circulation during high-demand periods.

Unit-level demand and device availability integration

Unit-level demand for medical equipment depends on patient census, acuity, admissions, discharges, transfers, procedural returns, and temporal patterns within each ward or service line. Bed-demand forecasting studies demonstrate that operational demand can be projected at hospital or ward levels using historical and real-time indicators [6, 8]. Intensive care and short-term bed-planning models further show that demand forecasting can support resource planning when interpreted within operational constraints [7, 19]. Linking these demand forecasts to current device availability would allow equipment managers to anticipate shortages by unit and device type rather than relying on retrospective utilization reports.

Framework Overview

High-level architecture

The proposed framework begins with real-time ingestion of RTLS coordinates, procedure schedule updates, computerized maintenance management events, ADT and census feeds, and device inventory records. RTLS data provide spatial visibility into device location, while procedure schedules supply forward-looking information about when procedural demand will occur [1, 4]. Maintenance records constrain the available device pool by identifying equipment that may be unavailable because of service, repair, or downtime [5]. These streams are processed through a fusion engine that would produce rolling utilization forecasts, shortage alerts, and recommended allocation actions for each device type and hospital unit.

Figure 1 illustrates the end-to-end artificial intelligence framework for predicting medical equipment utilization through the integration of real-time location data, procedural demand signals, maintenance constraints, and unit-level forecasts into operational decision support.

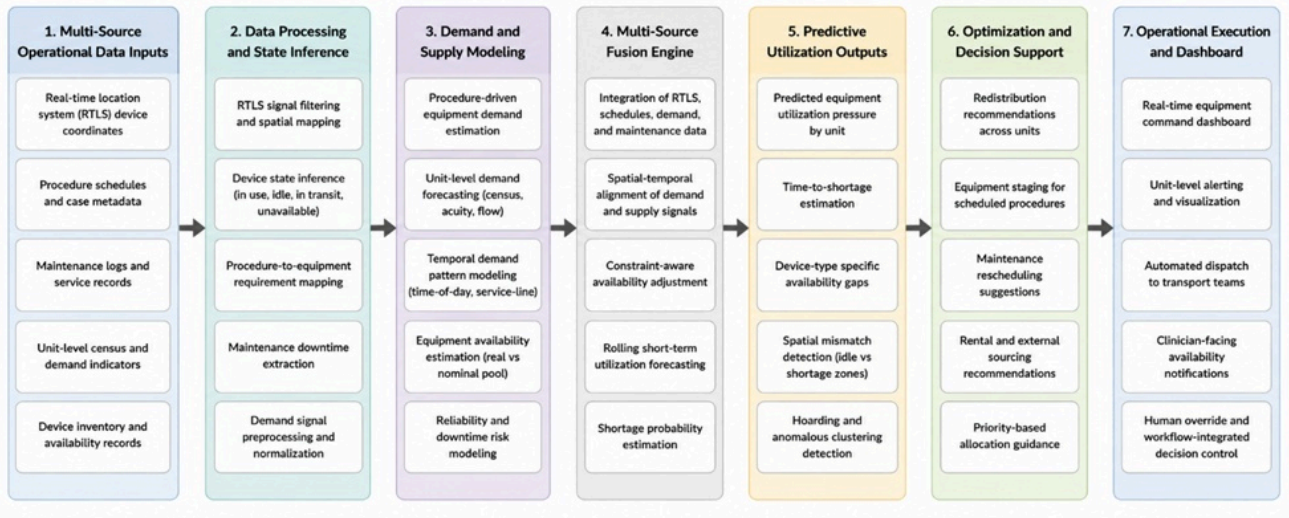


Figure 1. Artificial Intelligence Framework for Predicting Medical Equipment Utilization and Shortage Risk in Hospital Environments

Core input streams and outputs

The core inputs include device location and status, scheduled cases with expected equipment requirements, maintenance work orders, unit census projections, and current inventory counts. Forecasting studies in bed management show how census and demand signals can be translated into expected resource pressure, while operating room analytics demonstrate how scheduled care activity can inform future resource timing [10, 20]. The framework would convert these inputs into outputs such as predicted utilization pressure, time-to-shortage, expected availability gaps, and suggested redistribution actions. These outputs should be interpreted as decision-support signals rather than automatic substitutes for local operational judgment.

Table 1 presents the multi-source data streams and their distinct operational roles in constructing predictive medical equipment utilization signals.

Table 1. Multi-Source Data Contributions and Operational Roles in Predictive Medical Equipment Utilization Framework

Data Source	Core Variables	Operational Signal Type	Contribution to Prediction	Key Limitation	Integration Role
RTLS Data	Coordinates, dwell time, movement paths	Real-time spatial signal	Device location and movement patterns	Signal noise, coverage gaps	Enables state inference and spatial availability
Procedure Schedules	Case type, timing, specialty	Forward-looking demand signal	Predicts procedural equipment needs	Schedule changes, variability	Drives anticipatory staging decisions
Maintenance Logs	Service dates, failures, downtime	Availability constraint signal	Identifies unavailable or at-risk devices	Incomplete logging, lag	Adjusts effective equipment pool
Unit-Level Demand	Census, acuity, admissions	Aggregate demand signal	Predicts unit-level pressure	Forecast uncertainty	Aligns demand with location-based supply

Inventory Records	Device counts, identifiers	Baseline availability signal	Defines nominal equipment pool	Static representation	Anchors supply estimation
Device Status Systems	Cleaning, repair, reservation	Operational readiness signal	Refines practical availability	Fragmented systems	Improves real-world usability estimation

Design principles

The framework should be real time, resilient to sensor dropout, transparent to operational users, and aggregated at levels that are meaningful for clinical work. RTLS studies show that location systems can support workflow visibility, but they also require careful handling of signal latency, imperfect coverage, and contextual interpretation [3, 21]. Predictive outputs should therefore be organized by device type, unit, urgency, and actionability rather than by raw data streams. Command-center approaches reinforce the importance of connecting analytics to operational workflows so that predictions lead to staging, retrieval, maintenance adjustment, or dispatch decisions [14].

Real-Time Location and Device Availability Integration

RTLS data processing and state inference

RTLS data processing would begin by filtering raw location pings and mapping device observations to hospital zones such as patient rooms, clean storage, operating suites, imaging areas, corridors, and maintenance spaces. Asset-tracking studies show that RTLS can identify where equipment is located, but predictive use requires inference about what the location means operationally [1, 3]. A device located in a patient room may be in active use, while a device in a hallway may be idle, awaiting cleaning, or in transit. The framework would therefore infer states such as in use, idle, parked, moving, unavailable, or potentially misplaced by combining location, dwell time, movement history, and contextual rules.

Device availability record aggregation

Device availability cannot be inferred from location alone because a visible device may still be broken, reserved, contaminated, awaiting cleaning, or required for a scheduled case. The framework would therefore aggregate RTLS-derived status with inventory records, charge or docking data, maintenance status, and device identifiers. Studies of staff and asset movement demonstrate that location information becomes more useful when interpreted within clinical workflow rather than as isolated coordinates [2, 16]. By combining location and status records, the framework could estimate the practically available equipment pool more accurately than systems that only report where devices were last seen.

Detecting anomalous equipment movement and hoarding

Anomalous movement detection would compare expected device flows with observed clustering, prolonged dwell time, and repeated removal from central circulation. RTLS-based operational visibility can reveal hidden patterns such as devices accumulating in low-demand areas, remaining in unauthorized storage, or failing to return to central pools [1]. These patterns matter because hoarding may create apparent scarcity even when total inventory is sufficient. The framework would treat hoarding detection as an operational support function, using alerts to guide retrieval and redistribution while avoiding punitive interpretations of local workarounds [15].

Procedure Schedules and Unit-Level Demand Modelling

Extracting equipment requirements from procedure schedules

Procedure schedules can be converted into equipment demand signals by mapping case type, specialty, procedural location, expected duration, and historical equipment use to likely device requirements. Machine learning studies of surgical case duration show that scheduled case information can support predictions about timing and resource use in procedural environments [4, 10]. Additional work on operating room usage estimation reinforces the idea that procedural schedules contain structured information relevant to future operational demand [11]. In the proposed framework, these schedule-derived signals would help determine when specific equipment should be staged near operating rooms, imaging suites, endoscopy areas, or post-procedure recovery locations.

Forecasting unit-level demand from census and acuity

Unit-level equipment demand would be estimated from projected census, admissions, discharges, transfers, patient acuity, service-line mix, and time-of-day or day-of-week patterns. Hospital bed-demand models show that patient flow indicators can be used to anticipate where resource pressure is likely to emerge [6, 8]. Forecasts of intensive care occupancy and short-term bed needs further demonstrate that operational planning can benefit from demand estimates before capacity constraints become visible at the bedside [7, 19]. The same conceptual approach could be extended to equipment planning by associating expected patient volume and acuity with likely needs for pumps, monitors, beds, respiratory devices, and other mobile assets.

Synthesizing demand and supply forecasts

The framework would synthesize procedure-derived demand and unit-level demand forecasts with the real-time equipment supply map. Schedule-based models would indicate when procedural areas are likely to need devices, while census-based models would indicate where ward-level demand is expected to increase [10, 22]. Maintenance and reliability models would then adjust the available pool by accounting for devices that may be out of service, awaiting repair, or scheduled for preventive maintenance [13, 18]. By combining these signals, the framework could identify probable shortages early enough to support staging, redistribution, rental planning, or maintenance rescheduling before staff report that equipment is unavailable.

Maintenance Logs and Downtime Forecasting

Planned maintenance impact on equipment pools

Planned preventive maintenance can temporarily remove devices from circulation even when inventory records still show those devices as owned and assigned to the hospital. Predictive maintenance studies emphasize that service schedules and maintenance histories are important operational signals because they indicate when equipment should not be counted as fully available [5]. In the proposed framework, computerized maintenance management records would be aligned with RTLS and inventory data so that a device scheduled for inspection, calibration, repair, or cleaning is treated as unavailable during the relevant planning window. This adjustment would allow utilization forecasts to reflect the effective equipment pool rather than the nominal inventory count.

Unplanned downtime and reliability modelling

Unplanned downtime creates uncertainty because a device may fail during a period when demand is expected to be high. Medical device failure prediction studies suggest that historical repairs, recurring faults, device age, and maintenance patterns can inform estimates of future reliability risk [12, 18]. The framework could use survival-oriented or classification-oriented modelling to estimate whether a device is likely to become unavailable during a given time window, while remaining cautious about local validation requirements. Such reliability estimates would not replace biomedical engineering judgment, but they would help equipment managers anticipate which devices should be excluded from critical allocation plans.

Integrating downtime forecasts into utilization predictions

Downtime forecasts would be integrated into utilization prediction by reducing the number of devices considered operationally available in each unit and device category. Predictive maintenance approaches show that failure analysis and maintenance prioritization can support more proactive equipment management when service data are linked to operational decision-making [13]. IoT-oriented maintenance models also suggest that connected monitoring and maintenance records can contribute to earlier recognition of availability risks [23, 24]. Within the proposed framework, maintenance forecasts could trigger recommendations to reschedule nonurgent service, substitute alternative devices, or stage additional equipment before a predicted shortage becomes clinically disruptive.

Predictive Utilization Engine and Resource Optimization
Multi-source fusion and short-term utilization forecasting

The predictive utilization engine would combine RTLS-derived state inference, procedure-schedule demand, unit-level census forecasts, maintenance risk estimates, and device availability records into rolling short-term forecasts. Bed-demand and operating room prediction studies show that operational forecasts can be built from temporal care-delivery patterns, while RTLS research demonstrates that real-time location data can add spatial context to those forecasts [3, 4, 6]. Maintenance prediction would further constrain the forecast by identifying devices that may appear in inventory but should not be assumed available [5]. The engine would therefore estimate utilization pressure and time-to-shortage as conceptual decision-support outputs, not as experimentally proven performance measures.

Table 2 outlines the analytical functions and corresponding decision outputs across each layer of the predictive equipment utilization pipeline.

Table 2. Analytical Functions and Decision Outputs across the Predictive Equipment Utilization Pipeline

Framework Layer	Analytical Function	Input Dependencies	Output Type	Operational Decision Supported	Human Oversight Requirement
Data Processing	Signal filtering and normalization	RTLS, schedules, maintenance	Cleaned and structured data	Data reliability assurance	Low
State Inference	Device state classification	RTLS + contextual rules	Device availability states	Identification of usable equipment	Medium
Demand Modeling	Forecasting procedural and unit demand	Schedules, census	Demand projections	Anticipatory resource planning	Medium
Supply Modeling	Availability and reliability estimation	Inventory, maintenance	Effective equipment pool	Capacity planning	High
Fusion Engine	Multi-source integration and forecasting	All inputs	Utilization predictions	Early shortage detection	High
Optimization Layer	Allocation and redistribution logic	Forecast outputs	Action recommendations	Resource coordination decisions	Very High

Dashboard & Execution	Visualization and alerting	All outputs	Alerts and dashboards	Dispatch and operational response	Very High
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Proactive redistribution and rental recommendations

When a shortage is predicted, the framework would recommend redistribution from lower-demand areas to higher-demand units, early staging near procedural locations, or rental planning when internal supply is unlikely to be sufficient. Optimization research in patient and operating room assignment shows that predictive analytics can be paired with allocation logic to support more coordinated resource decisions [20, 22]. Centralized command-center models further suggest that predictions are most useful when they are translated into operational actions that dispatchers, equipment managers, and clinical leaders can understand [14]. The framework would therefore present recommendations with urgency, rationale, and workflow context rather than producing isolated risk scores.

Operational Dashboard and Automated Decision Support

Equipment command dashboard

The operational dashboard would display real-time device locations, inferred availability states, unit-level utilization pressure, predicted shortage alerts, and recommended redistribution actions. Command-center research shows that centralized visual management can support hospital-wide coordination when multiple operational data streams are represented in a shared environment [14]. Reviews of centralized management systems similarly emphasize the value of real-time data, predictive analytics, and information technology for improving operational awareness [15]. In this framework, the dashboard would function as a practical bridge between the predictive engine and the teams responsible for equipment staging, dispatch, cleaning, maintenance, and escalation.

Automated dispatch and clinician-facing alerts

Automated dispatch support would connect shortage predictions to porter systems, equipment distribution teams, biomedical engineering workflows, and nursing unit dashboards. RTLS studies indicate that real-time location information can support operational monitoring, but alert design must reflect clinical context to avoid unnecessary interruption or mistrust [2, 21]. Clinician-facing alerts should therefore focus on actionable information, such as when a requested device is being dispatched, when an alternative is available nearby, or when a predicted shortage requires early escalation. The framework should preserve human override because local clinical priorities may justify decisions that differ from algorithmic recommendations.

Evaluation Strategy

Predictive accuracy of utilization and shortage forecasts

Evaluation should examine whether the framework can predict utilization pressure and shortage events with sufficient reliability to support operational planning. Studies of hospital bed forecasting and operating room case prediction commonly evaluate forecast quality by comparing predicted demand or duration with observed operational outcomes [8, 10]. For this framework, appropriate evaluation would compare predicted utilization states with later observed device use, shortage reports, dispatch requests, and RTLS-confirmed movement patterns. The article remains conceptual, so these metrics are proposed as future evaluation criteria rather than reported results.

Operational impact on equipment availability and efficiency

Operational evaluation should assess whether the framework is associated with better equipment availability, fewer search delays, reduced hoarding, more timely redistribution, and more efficient rental decisions. RTLS asset-tracking studies provide a basis for measuring device movement and location visibility, while command-center work suggests that operational impact should be evaluated at the level of workflow coordination rather than only algorithmic output [1, 14]. Predictive maintenance studies also indicate that service-related availability should be considered when evaluating whether a device pool is truly usable [12, 13]. Future implementation studies should therefore examine both equipment visibility and the practical consequences of acting on utilization forecasts.

Usability and trust among equipment managers and clinicians

Usability evaluation should examine whether equipment managers, nurses, biomedical engineering staff, transport teams, and clinical leaders understand and trust the framework's recommendations. Healthcare RTLS reviews note that technology adoption depends not only on technical feasibility but also on workflow fit, perceived usefulness, and the quality of operational interpretation [3]. Studies involving real-time location and emergency department workflows further suggest that location-based systems must be integrated carefully so they support care rather than add surveillance concerns or alert burden [21]. Surveys, interviews, and focus groups would therefore be needed to assess dashboard clarity, alert usefulness, override behavior, and confidence in recommended redistribution actions.

Limitations

RTLS infrastructure and coverage gaps

A major limitation is that RTLS infrastructure may not cover every clinical area, device category, or workflow transition point. Reviews and feasibility studies of RTLS in healthcare show that signal quality, tagging practices, latency, and environmental constraints can affect the usefulness of location data [1, 3]. Dense hospital environments may create interference, and untagged devices may remain outside the predictive system even when they are operationally important. The framework must therefore be designed to handle missing signals, uncertain location states, and partial deployment rather than assuming complete real-time visibility.

Clinical workflow integration and human factors

Clinical workflow integration is another major limitation because equipment redistribution can conflict with local preferences, perceived unit safety, and informal strategies used by staff to protect access to scarce devices. Studies of contextual computing and real-time workflow monitoring indicate that location-aware systems must be interpreted within the social and clinical environment in which work occurs [16]. Command-center and centralized management approaches also depend on whether staff trust the information presented and whether recommendations align with practical authority, staffing, and escalation pathways [14, 15]. The framework should therefore support explanation, override, and local adaptation rather than imposing automated orchestration without human judgment.

Conclusion

The proposed Artificial Intelligence Framework for predicting medical equipment utilization describes how hospitals could move from reactive device searching to anticipatory equipment planning. By integrating real-time location data, procedure schedules, maintenance logs, unit-level demand forecasts, and device availability records, the framework offers a conceptual model for predicting where and when equipment shortages may emerge.

A key strength of the framework is its multi-source design. Location data provide spatial awareness, schedules provide forward-looking procedural demand, maintenance logs define availability constraints, and unit-level forecasts indicate where care pressure is likely to increase. When these streams are fused into a common prediction layer, equipment managers could receive earlier and more actionable signals about utilization risk.

Important challenges remain before such a framework could be implemented at scale. Hospitals would need reliable RTLS coverage, interoperable data feeds, accurate device identifiers, and governance processes for determining how recommendations are acted on. Cultural acceptance would also be essential because equipment movement affects daily clinical routines and may require staff to trust automated recommendations while retaining authority to override them.

Future work should focus on pilot implementations in high-acuity wards, procedural areas, and surgical suites where equipment shortages are especially disruptive. These pilots should evaluate predictive reliability, operational usability, staff trust, and return on investment without assuming that technical performance alone will guarantee clinical adoption. A carefully implemented framework could support a more data-driven, anticipatory, and coordinated hospital equipment supply chain.

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