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Smart Hospital Artificial Intelligence System for Predicting Nurse Call Button Demand Using Patient Acuity Levels, Room Location, Prior Call Frequency, Time-of-Day Patterns, and Unit Staffing Ratios

Daniel Fischer^{1*}, Laura Meier¹, Thomas Braun², Stefan Koch², Felix Roth¹

Abstract

Nurse call buttons are a core communication channel through which hospitalised patients request assistance, reassurance, symptom support, and routine care. When call demand is high, nurses may experience overload, interruptions, and competing priorities that delay responses to urgent needs. Current approaches to call demand management are largely reactive and shift based. They often overlook rapid fluctuations driven by patient acuity, prior call behaviour, room geography, time-of-day routines, and staffing conditions. This article proposes a smart hospital AI system for short-term prediction of nurse call button demand at the room or unit-zone level. The framework is conceptual and system oriented, with emphasis on how operational data streams could support proactive nursing workflow decisions. The system includes a patient acuity scoring module, call history learner, circadian pattern analyser, room-location spatial modeller, staffing-ratio adjuster, and real-time demand forecasting dashboard. Together, these components would translate fragmented operational signals into interpretable demand forecasts. The proposed system would support proactive allocation of nursing resources by identifying rooms or zones likely to generate elevated call demand. It could also guide anticipatory rounding, help reduce avoidable non-urgent calls, and support more balanced workload distribution. A demand-driven nursing workflow would move smart hospital operations beyond reactive response to patient-initiated requests. Predictive nurse call intelligence offers a pathway toward more responsive, equitable, and resilient inpatient care.

Keywords Artificial intelligence, Smart hospital, Nursing workload, Demand forecasting, Nurse call buttons, Patient acuity

*Correspondence:

Daniel Fischer

daniel.fischer@outlook.com

¹ Department of Healthcare Informatics and Data Engineering, Faculty of Medicine, University of Freiburg, Freiburg, Germany

² Department of Intelligent Medical Systems, Faculty of Engineering, Karlsruhe Institute of Technology, Karlsruhe, Germany

Introduction

Nurse call lights remain a primary mechanism through which hospitalised patients initiate contact with nursing staff, yet frequent call activity can fragment work, increase interruption burden, and intensify perceived workload. Studies of call-light technologies and communication systems show that patient-initiated calls are not merely technical signals but workflow events that require interpretation, prioritisation, and timely action [1-3]. When call volume rises, nurses may face

difficulty distinguishing routine requests from clinically meaningful changes in patient need. These pressures can contribute to missed care, dissatisfaction, and stress in already demanding inpatient environments [4-6].

Conventional staffing approaches are usually organised around census, shift templates, and professional judgement rather than minute-to-minute demand variation. Such static models may not capture micro-fluctuations created by toileting needs, pain reassessment, medication timing, family requests, or mobility limitations [7, 8]. Spatial layout and unit geography can further influence how visible or accessible a patient is to staff, making room-level demand difficult to infer from unit-level averages alone. As a result, nursing leaders may recognise workload escalation only after call queues, delays, or staff strain have already emerged [9, 10].

Smart hospital infrastructures increasingly generate operational signals that could be used to anticipate demand rather than merely document it. Electronic health records, acuity indicators, admission-discharge-transfer data, call logs, and real-time workflow technologies can collectively describe who is likely to need help, where they are located, and when demand is likely to peak [11-13]. Machine learning research in clinical deterioration, workload prediction, and health service operations demonstrates how heterogeneous hospital data streams could support prospective decision support when designed for clinical interpretability [14-16]. These signals create an opportunity to reframe nurse call management as a predictive operational problem.

This article proposes an AI systems framework that continuously forecasts nurse call button demand at the room or zone level. The system would integrate patient acuity, prior call frequency, time-of-day patterns, room location, and unit staffing ratios to produce short-term demand estimates for charge nurses and frontline teams. Rather than replacing nursing judgement, the framework would provide anticipatory situational awareness that supports proactive rounding and staff redistribution. Its core contribution is a conceptual architecture for demand-driven nursing operations in smart hospitals.

Background

Nurse call systems and workflow interruption

Nurse call systems function as patient-initiated communication infrastructure, allowing patients to request assistance for pain, toileting, repositioning, alarms, social support, and safety concerns. Observational and implementation studies show that call systems influence how staff perceive urgency, allocate attention, and coordinate responses across rooms and roles [3-5]. Wireless and smartwatch-based notification systems illustrate the movement from centralised audible alerts toward distributed, mobile, and digitally mediated response models [1, 2]. However, even improved notification tools can add cognitive load if they transmit more signals without forecasting which demands are likely to accumulate.

Patient acuity and its relationship to call demand

Patient acuity can shape call demand because higher clinical risk, mobility limitations, medication burden, delirium risk, and dependency needs often increase assistance requirements. Machine learning studies using electronic records for falls, pressure injury, readmission, deterioration, and mortality prediction demonstrate that structured clinical indicators can be transformed into risk vectors relevant to nursing surveillance [10, 17, 18]. In a nurse call framework, early warning scores, fall risk, mobility status, pressure injury risk, and comorbidity burden would serve as proxies for likely care-seeking or assistance-seeking behaviour. This conceptual link allows acuity to become an operational signal rather than only a clinical severity descriptor [19, 20].

Temporal patterns in call frequency

Call demand is likely to follow ward rhythms because inpatient care is organised around medication passes, assessments, meals, hygiene, visiting periods, handovers, and overnight routines. Time-stamped operational modelling in health services has shown the importance of temporal structure when predicting demand and resource pressure [12, 21].

A nurse call system could therefore treat hour of day, shift phase, weekday context, and proximity to recurring care activities as predictors of expected call density. Temporal modelling would be especially useful when call frequency rises during predictable routines but has different implications depending on concurrent staffing [22, 23].

Room location and spatial factors

Room location may influence call button demand because distance from the nurses' station, visibility, isolation status, bathroom access, and hallway placement shape how patients seek help and how staff notice emerging needs. Research on call systems and residential care environments suggests that patient-initiated signals are embedded in physical and organisational context, not only individual preference [5, 7, 8]. Spatial demand modelling in health operations also supports the idea that location and neighbourhood effects can be used to anticipate service requests across geographic units [12]. A smart hospital framework should therefore treat each room as a spatial node with stable architectural features and dynamic occupant-related risk.

Unit staffing ratios and real-time workload balancing

Unit staffing ratios modify the operational meaning of a predicted call load because the same number of calls can be manageable with adequate staff and destabilising with reduced coverage. Evidence linking nurse staffing to hospital outcomes and readmissions suggests that staffing is not a background variable but an active determinant of care capacity and workload resilience [11]. In a nurse call forecasting system, current nurse-to-patient ratio, skill mix, assignment geography, and break coverage would adjust the priority assigned to predicted demand. This would allow the system to forecast not only expected call volume but also the burden that volume may impose on available staff [24, 25].

System Overview

High-level architecture

The proposed architecture would ingest nurse call logs, EHR-derived acuity indicators, admission-discharge-transfer room data, and staffing roster information into a secure operational analytics layer. A prediction engine would use these inputs to estimate short-term call demand for each room or zone over the next operational window, such as the next thirty to sixty minutes [13, 16]. The output would be displayed as an interpretable demand map rather than as an opaque technical score. This architecture follows the broader movement toward clinically applicable AI systems that combine real-time data with decision support designed for frontline users [14, 15].

Figure 1 illustrates the proposed smart hospital AI architecture for translating room-level operational data into interpretable nurse call demand forecasts and governed workflow support.

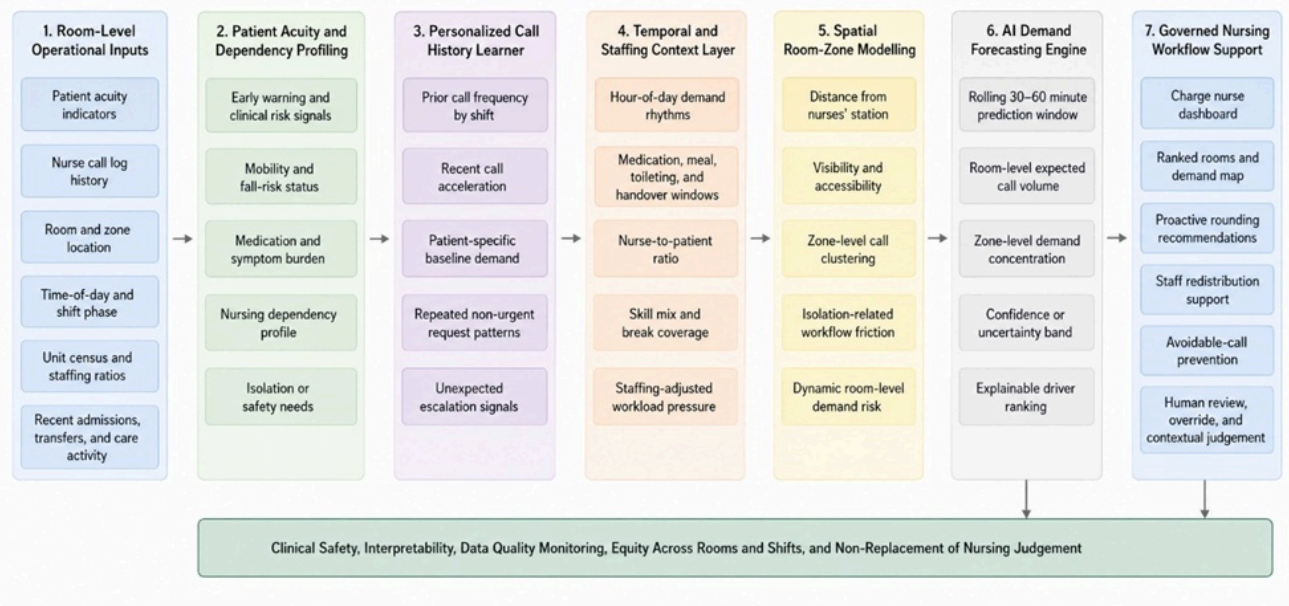


Figure 1. Smart hospital AI architecture for forecasting nurse call button demand using acuity, call history, temporal routines, room location, and staffing context.

Core inputs and outputs

Core inputs would include patient acuity scores, individual call history, timestamp features, room or zone coordinates, unit census, and current staffing ratios. The system would output predicted call demand per room or unit zone, accompanied by uncertainty language that helps charge nurses decide whether proactive rounding or staff redistribution is warranted [26, 27]. These outputs should be framed as decision-support signals rather than deterministic instructions. Model facts, transparent input summaries, and clear explanation of why a room is flagged would be necessary for clinical trust and safe adoption [27].

Table 1 decomposes the proposed nurse call demand prediction system into functional modules, operational questions, interpretable outputs, and workflow value.

Table 1. Functional Decomposition of the Nurse Call Demand Prediction Framework

Framework component	Primary operational question addressed	Key input signals	Analytical function	Interpretable output for nursing teams	Workflow value
Patient acuity scoring module	Which patients are more likely to need assistance because of clinical risk or dependency?	Early warning signals, mobility status, fall risk, medication burden, nursing dependency	Converts clinical and dependency indicators into an operational acuity vector	“High assistance likelihood due to mobility limitation and symptom burden”	Supports anticipatory rounding based on care need rather than call volume alone
Call history learner	Is the current call pattern normal for this patient or newly increasing?	Prior call frequency, recent calls, shift-specific baseline,	Builds personalized room/patient call baselines and detects deviations	“Call activity above recent baseline”	Distinguishes persistent high need from emerging escalation

		unresolved repeated requests			
Circadian pattern analyser	Is demand expected because of routine ward timing?	Hour of day, shift phase, medication timing, meal periods, handover windows	Models predictable temporal peaks in call demand	“Expected demand peak during morning care window”	Helps plan proactive rounding before predictable surges
Room-location spatial modeller	Where is demand likely to cluster geographically?	Room coordinates, zone assignment, distance from nurses' station, visibility, isolation status	Detects room-level and zone-level spatial concentration	“Elevated demand in far hallway zone”	Reduces avoidable walking, waiting, and uneven response burden
Staffing-ratio adjuster	Can current staff capacity absorb predicted demand?	Nurse-to-patient ratio, skill mix, assignment geography, break coverage, census	Converts predicted call count into staffing-adjusted workload pressure	“Moderate call volume but high pressure due to reduced staffing”	Supports redistribution of staff before overload emerges
Forecasting dashboard	What should the charge nurse know now?	Integrated model outputs, uncertainty bands, driver rankings	Displays ranked rooms, zones, demand explanations, and confidence	“Top rooms by predicted demand with main contributing factors”	Provides actionable situational awareness without replacing judgement

Design principles

The system should be real-time, low-latency, interpretable, vendor-agnostic, and compatible with existing nurse call infrastructure. Because nursing workflows are complex and interruption sensitive, the design should avoid adding excessive alerts or dashboards that compete with patient care [3, 9]. The interface should prioritise clarity for charge nurses by showing high-demand rooms, expected contributing factors, and suggested proactive actions. Human-centred AI principles are essential because nursing staff must be able to question, override, and contextualise system recommendations [26, 27].

Patient Acuity and Call History Modelling

Acuity score construction and integration

The acuity module would aggregate existing indicators such as early warning signals, mobility status, fall risk, pressure injury risk, medication complexity, isolation status, and nursing dependency into a unified acuity vector. Prior predictive modelling work in falls, pressure injury, deterioration, and hospital mortality shows that clinically meaningful risk features can be extracted from routine EHR data for operational decision support [10, 17-19]. In the proposed framework, this vector would not diagnose deterioration or replace clinical judgement. Instead, it would contextualise whether a patient is likely to generate higher assistance demand through physical dependency, symptom burden, or safety needs [20].

Personalised call baselines from prior frequency

The call history learner would estimate each patient's personalised baseline from previous calls across recent shifts, while recognising that high call frequency may reflect dependency, anxiety, pain, unmet needs, communication barriers, or environmental factors. Call-light research indicates that patient-initiated calls have heterogeneous meanings and that staff interpretation depends on context and prior experience with the resident or patient [3, 4, 7]. A personalised baseline would help distinguish patients whose call frequency is consistently high from those whose call activity is newly increasing. This approach would support respectful anticipation of need rather than labelling frequent callers as operational problems.

Detecting changing acuity and escalation patterns

A sudden increase in call frequency could function as an early operational signal that a patient's condition, comfort, mobility, or perceived safety has changed. AI systems for clinical deterioration, acute kidney injury, sepsis, and in-hospital cardiac arrest demonstrate that temporal changes in routine data can contain useful early-warning information [14, 15, 18, 25]. In the proposed framework, the system would feed unexpected call escalation back into acuity review by prompting staff to consider whether the pattern reflects clinical change, unmet symptom control, or care-process mismatch. This feedback loop would connect operational demand prediction with nursing surveillance without claiming diagnostic certainty.

Time-of-Day and Unit Staffing Integration

Circadian and shift-based call demand patterns

The circadian analyser would model expected call density across the twenty-four-hour cycle while accounting for unit routines such as morning assessments, meals, toileting rounds, medication administration, visiting periods, and overnight quiet hours. Health service prediction studies show that demand forecasting benefits from representing temporal regularity rather than treating events as randomly distributed [12, 21]. In nurse call forecasting, time-of-day features would help distinguish predictable demand peaks from unusual surges. This distinction matters because predictable peaks may be addressed through planned rounding, whereas unusual surges may require immediate reassessment of workload and patient condition.

Real-time staffing-ratio adjustments

The staffing-ratio adjuster would modify demand interpretation according to available nurses, support staff, skill mix, break schedules, and assignment geography. Staffing research indicates that workforce levels and nursing capacity shape outcomes and care reliability, which supports incorporating staffing ratios into operational forecasting rather than using call predictions alone [11, 24]. A projected call load that is acceptable during full staffing may become operationally risky during handover, breaks, admissions, or temporary staff shortages. The system would therefore present staffing-adjusted demand pressure rather than only predicted call counts.

Synthesising temporal and staffing context for demand forecasting

The forecasting layer would synthesise temporal patterns and staffing context by recognising that identical call demand can impose different burdens depending on when it occurs and who is available to respond. For example, call clustering during shift change or medication administration would be weighted differently from the same activity during a stable mid-shift period [19, 20]. This logic aligns with broader AI-enabled hospital operations, where predictive signals are most useful when embedded in the constraints of real workflows and resource availability [16, 26, 28]. The goal is to help charge nurses anticipate pressure points before call queues, delays, or avoidable interruptions accumulate.

Room Location and Spatial Correlation Effects

Geographical demand heatmapping

The spatial modeller would translate room location into a demand heatmap that identifies zones where call burden may concentrate. Rooms farther from the nurses' station, less visible from common work areas, or requiring additional isolation procedures may generate higher operational friction even when clinical acuity is similar [5, 7, 8]. Spatial prediction methods used in health service demand modelling support the idea that location can be treated as an operational feature rather than a static background descriptor [12]. In this framework, geography would help the charge nurse see where proactive rounding could reduce avoidable walking, waiting, and repeated call activation.

Neighbourhood effects and call clustering

Neighbourhood effects may occur when calls in one room are associated with subsequent calls from nearby rooms due to shared noise, toileting routines, family presence, or clustered care activities. The system would represent rooms as connected spatial nodes so that recent call activity in one area could increase attention to adjacent rooms or hallway segments [12]. Evidence from call-light and residential care studies suggests that patient-initiated requests are socially and spatially situated, making neighbouring context relevant to interpretation [4, 7]. A spatial autoregressive component would therefore capture call clustering without assuming that every adjacent patient has the same underlying need.

Dynamic room-level risk scores

The room-level risk score would combine stable room attributes with dynamic occupant data, including acuity, prior call frequency, recent escalation, time-of-day context, and staffing pressure. This score would not label the room or patient as problematic, but would indicate where demand may require anticipatory nursing attention [10, 17, 20]. Because explainability is essential for clinical adoption, the dashboard should show whether a high score is mainly driven by patient dependency, recent call acceleration, spatial isolation, or low staffing coverage [27]. Such transparency would allow nurses to validate the recommendation against bedside knowledge.

Real-Time Demand Forecasting and Alert Prioritisation

Rolling demand forecasts and confidence bands

The forecasting engine would update at short intervals and produce rolling estimates of expected call demand for rooms, hallways, or care zones. Conceptual candidate models could include interpretable count models, gradient-boosted decision trees, or online learning methods, selected according to local governance, transparency, and integration requirements [16, 21]. The system should express uncertainty qualitatively or through interpretable bands so that nurses understand when predictions are stable versus tentative [27]. This design would keep forecasting useful for operational awareness without implying that call behaviour can be predicted with deterministic precision.

Prioritising alerts for charge nurse intervention

Alert prioritisation should occur only when predicted demand exceeds what current staffing and workflow context can reasonably absorb. Rather than generating another interruptive alarm stream, the system would recommend targeted proactive actions such as rounding on specific rooms, adjusting staff assignments, or checking whether comfort, toileting, pain, or positioning needs are already anticipated [3, 6]. Research on nursing AI and clinical decision support emphasises that alerts must be actionable, interpretable, and aligned with professional judgement to avoid burdening clinicians [22, 26]. The priority logic should therefore elevate only demand patterns that are operationally meaningful.

Clinical Workflow Integration and Proactive Staff Allocation

Charge nurse dashboard and mobile integration

The charge nurse dashboard would present a simple heatmap, a ranked room list, and concise explanations of the factors contributing to predicted demand. Integration with mobile devices, central monitors, and existing call-light platforms would allow the system to support workflow without requiring nurses to consult a separate analytics environment [1, 2, 6]. Human-centred design is especially important because communication technologies can either streamline response or add extra cognitive burden when poorly integrated [3, 9]. The interface should therefore privilege rapid interpretation, clear accountability, and easy dismissal or confirmation of recommendations.

Linking demand forecasts to reduction in non-urgent calls

The proactive allocation mechanism would connect forecasts to interventions such as toileting assistance, pain reassessment, repositioning, supply checks, family communication, or reassurance rounding. If a room is expected to generate elevated non-urgent calls, an anticipatory visit could address needs before the call button is pressed, while preserving the patient's right to request help at any time [4, 7]. Evaluation should examine whether proactive rounding changes patterns of call demand, response workload, and staff experience without suppressing legitimate patient-initiated communication [5, 26]. The system would be judged by whether it improves care coordination rather than by whether it simply reduces call counts.

Evaluation strategy

Table 2 presents a multidimensional evaluation matrix for assessing forecast validity, operational impact, usability, equity, and safe implementation of the proposed nurse call demand prediction system.

Table 2. Evaluation Matrix for Forecast Validity, Workflow Impact, and Safe Implementation

Evaluation domain	Core evaluation question	Suggested measures	Required stratification	Interpretation principle	Implementation safeguard
Forecast accuracy	Do predicted room-level calls match observed demand?	Mean absolute error, root mean square error, Poisson deviance, calibration of prediction intervals	Shift, room zone, acuity level, staffing ratio	Accuracy must be judged by operational usefulness, not statistical performance alone	Recalibrate locally before deployment across new units
Demand pressure validity	Does the system correctly identify periods of workload strain?	Predicted demand-to-staff capacity ratio, queue formation, response delay risk	Handover, breaks, admissions, low-staffing periods	Call volume and workload pressure are not equivalent	Present staffing-adjusted pressure rather than raw call counts alone
Workflow impact	Does proactive use improve nursing operations?	Call response time, call clustering, rounding frequency, staff redistribution events	Unit type, weekday/weekend, day/night shift	Fewer calls are not automatically better	Distinguish avoidable routine calls from urgent patient advocacy calls
Nursing usability	Do staff understand and trust the system?	Usability surveys, interviews, dashboard	Charge nurses, bedside nurses, float staff, new staff	Trust requires transparency and clinical plausibility	Display top drivers and allow dismissal or override

		comprehension, alert burden			
Equity and fairness	Does performance vary across patients, rooms, or shifts?	Error by acuity group, room location, language needs, isolation status, dependency level	Patient dependency, room visibility, staffing level, unit zone	The system must not disadvantage less visible or more dependent patients	Monitor subgroup performance and prevent punitive interpretation
Behavioural adaptation	Does the system change how demand is expressed or recorded?	Verbal requests, undocumented care work, corridor interruptions, patient satisfaction	Pre/post implementation periods and staff role	Reduced button use may reflect shifted workload, not reduced need	Include qualitative workflow observation and patient-centred outcomes

Forecast accuracy metrics

Evaluation should begin with forecast validity, comparing predicted and observed calls per room and time window using appropriate count-model and calibration metrics. Metrics such as root mean square error, mean absolute error, Poisson deviance, and calibration of prediction intervals would be suitable for methodological assessment, but they should be interpreted as evidence of operational usefulness rather than stand-alone success [12, 21]. Because nursing workflows vary across units, accuracy should be examined separately by shift, room zone, acuity level, and staffing context [11, 24]. This would help determine whether the model supports equitable and reliable decision support across heterogeneous care environments.

Operational impact on call volume and response time

Operational evaluation should examine whether system-supported proactive rounding changes call volume, call response time, workload distribution, and perceived care reliability. A prospective implementation design, such as a stepped-wedge or phased rollout, would allow units to compare workflow before and after activation while accounting for local context [5, 6]. The evaluation should avoid assuming that fewer calls are always better, because some calls reflect appropriate patient advocacy or emerging clinical need [3, 4]. Therefore, impact assessment should distinguish avoidable routine calls from urgent or clinically meaningful requests.

Usability and acceptance by nursing staff

Usability evaluation should examine whether nurses trust the forecast, understand the explanation, and find the recommendations compatible with real workflow. Surveys, interviews, focus groups, and observation could assess perceived accuracy, fairness, alert burden, and effects on professional autonomy [9, 26]. Model facts labels and transparent presentation of inputs would support acceptance by helping users understand what the system does and does not know [27]. Staff feedback should also be used to refine thresholds, dashboard design, and escalation logic before broader implementation.

Limitations

Data granularity and system integration

A major limitation is that nurse call systems may not capture every relevant event with consistent granularity. Some systems may record call initiation but not call reason, response pathway, staff arrival, resolution, room transfer, or whether a need was handled without a button press. EHR acuity fields, admission-discharge-transfer feeds, and staffing rosters

may also be delayed, incomplete, or inconsistently structured across hospitals. These integration challenges mean the system should be implemented cautiously, with continuous data-quality monitoring and local validation.

Behavioural adaptation and gaming

A second limitation is behavioural adaptation by patients, families, or staff once the forecasting system becomes visible in routine operations. Proactive rounding may reduce button activations, but it may also shift demand into verbal requests, corridor interactions, or undocumented care work. Staff may also learn to respond to the dashboard in ways that change measured demand without necessarily improving patient experience. For this reason, evaluation should include qualitative workflow assessment, patient-centred outcomes, and safeguards against treating call reduction as the only goal.

Conclusion

The proposed smart hospital AI system frames nurse call button demand as a real-time operational forecasting problem. By integrating patient acuity, prior call frequency, time-of-day patterns, room location, and unit staffing ratios, it would help nursing teams anticipate where patient-initiated requests are likely to concentrate.

Its main strength is the combination of room-level granularity with multi-factor demand context. Rather than asking charge nurses to infer workload pressure from fragmented signals, the framework would provide a shared demand picture that supports proactive rounding, staff redistribution, and more balanced response planning.

Important challenges remain before such a system could be safely adopted. Data quality, workflow variation, behavioural change, interpretability, vendor integration, and multi-site validation all require careful attention.

Implementation pilots in acute medical-surgical units would be a practical next step for testing feasibility, usability, and operational value. Over time, open benchmarks for nursing demand prediction could help the field compare approaches and develop safer, more transparent AI tools for nursing operations.

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