

REVIEW

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Artificial Intelligence in Smart Hospital Management: A Systematic Review of Command Centers, Real-Time Workflow Monitoring, Operational Dashboards, and Automated Decision Support Systems

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Abstract

Smart hospitals increasingly combine artificial intelligence, real-time data streams, operational dashboards, and automated decision support to coordinate care delivery. These systems aim to improve hospital throughput, staff efficiency, resource use, and patient safety. This systematic review synthesised evidence on AI technologies used in smart hospital management from 2017 to 2023. The review focused on command centers, real-time workflow monitoring, operational dashboards, and automated decision support systems. A PRISMA 2020-compliant review process was used, including structured database searching, dual screening, and narrative synthesis. Extracted data covered study characteristics, AI methods, deployment maturity, data sources, integration patterns, and reported operational impact. The evidence base was concentrated on hospital command centers, predictive dashboards, and patient-flow analytics. Real-time workflow monitoring and automated decision support were less mature, and prospective evaluations of operational or clinical impact were uncommon. AI-enabled smart hospital management is technologically promising but remains unevenly implemented and weakly evaluated. Current evidence supports cautious adoption, local validation, and stronger evaluation designs before claims of sustained operational transformation are accepted.

Keywords Artificial intelligence, Decision support, Smart hospital, Command center, Real-time workflow monitoring, Operational dashboard

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Introduction

The smart hospital vision describes an operational environment in which artificial intelligence integrates administrative, clinical, logistical, and environmental data to support real-time coordination. Several studies described centralized command centers as visible expressions of this vision, using operational displays and predictive analytics to support bed management, patient flow, and resource allocation [1-3]. However, the evidence also suggests a persistent gap between aspirational smart hospital architecture and routine, integrated, AI-driven operational practice [4, 5].

Four components structure the field: command centers, real-time workflow monitoring, operational dashboards, and automated decision support. Command centers centralize situational awareness, real-time monitoring collects data from clinical workflows and location systems, dashboards translate data into operational views, and automated decision

support proposes or triggers management actions [6-8]. These components are interdependent because predictive dashboards and automated decision tools require reliable, timely data streams from EHR, ADT, RTLS, staffing, and logistics systems [5, 9].

Existing reviews and implementation reports have tended to examine one component at a time rather than the full smart hospital management stack. Prior work has considered command centers, real-time location systems, process mining, inpatient bed management, and prediction of length of stay as separate literatures [4, 6, 10-12]. This fragmentation limits understanding of whether AI-enabled hospital management is developing as an integrated operational model or as a set of disconnected digital tools.

The objective of this systematic review was to synthesise peer-reviewed literature from 2017 to 2023 on AI in smart hospital management, with emphasis on command centers, real-time workflow monitoring, operational dashboards, and automated decision support systems. The review is followed by defining eligibility criteria, applying structured screening, extracting study-level information, and narratively synthesising evidence by component and maturity level. Because the literature was heterogeneous in design, setting, technology, and outcome measurement, the review did not attempt meta-analysis.

Materials and Methods

Search strategy

Searches were structured around combinations of “smart hospital,” “hospital command center,” “real-time workflow monitoring,” “operational dashboard,” “predictive analytics,” “automated decision support,” “machine learning,” “artificial intelligence,” “bed management,” “patient flow,” and “real-time location system.” The strategy was designed to retrieve literature on centralized hospital operations, AI-enabled workflow visibility, prediction-driven dashboards, and decision support for bed, staffing, and logistics coordination. Targeted journals included medical informatics, health systems engineering, quality and safety, digital health, and clinical operations venues represented in the included references.

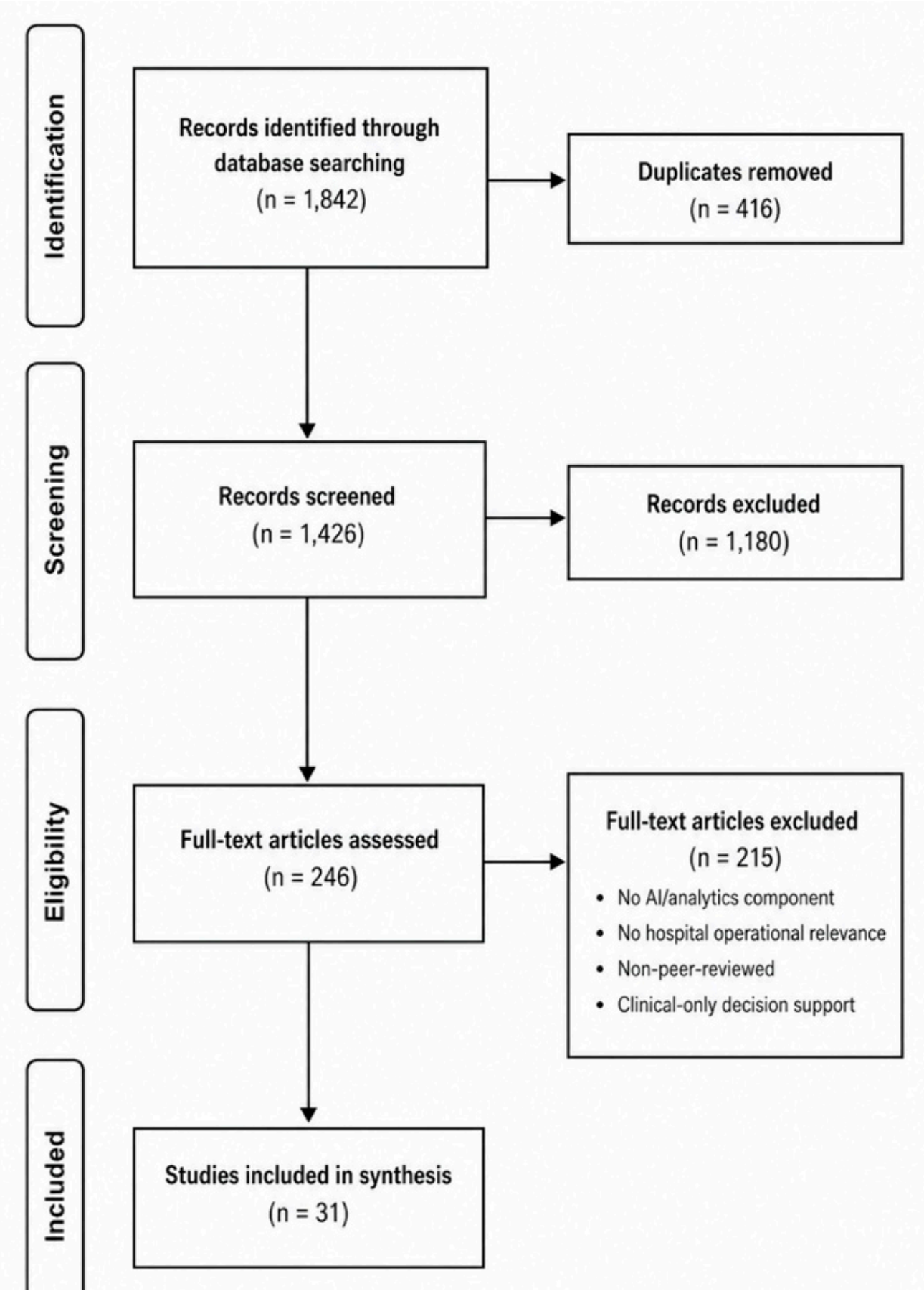
Inclusion and exclusion criteria

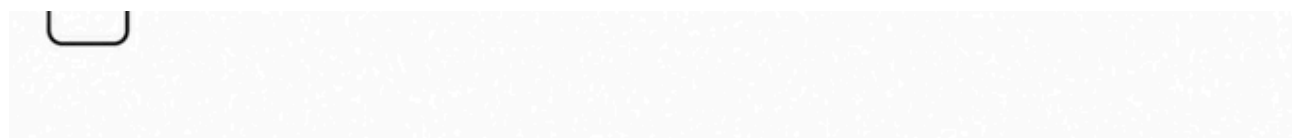
Eligible studies were peer-reviewed publications from 2017 to 2023 that addressed AI-driven or data-intensive smart hospital management in real hospital or hospital-relevant operational contexts. Studies were included when they described command centers, real-time workflow monitoring, operational dashboards, predictive operational models, automated decision support, or integration of smart hospital infrastructure. Publications were excluded when they were purely technical model-development papers without hospital operational relevance, lacked connection to patient flow or resource coordination, or addressed clinical decision support without an operational management component.

Screening and selection

Records were screened independently by two reviewers using titles, abstracts, and full texts, with disagreements resolved through discussion. The PRISMA flow identified 1,842 records, removed 416 duplicates, screened 1,426 titles and abstracts, assessed 246 full texts, and included 31 publications in the final synthesis. Full-text exclusions most often reflected lack of AI or analytics content, absence of hospital management relevance, non-peer-reviewed status, or focus on clinical diagnosis rather than operational coordination.

The study selection process is summarised in **Figure 1** following PRISMA 2020 guidelines





Data extraction captured publication year, setting, hospital type, smart hospital component, AI or analytics method, operational data sources, deployment status, evaluation design, and reported outcomes. Particular attention was given to whether systems used EHR, ADT, RTLS, sensor, staffing, logistics, or dashboard data, because integration across these sources is central to smart hospital maturity. Extracted outcomes included length of stay, patient flow, waiting time, bed occupancy, staff workflow, user experience, safety, and implementation barriers when these were reported.

Risk of bias assessment

Risk of bias was assessed narratively because included studies varied across implementation reports, observational evaluations, protocols, prediction studies, reviews, and operational analytics papers. For prediction-oriented studies, the assessment considered risks analogous to PROBAST domains, including participant selection, predictor availability, outcome definition, confounding, and analysis transparency. For implementation and command-center studies, emphasis was placed on uncontrolled before-and-after designs, vendor involvement, selective reporting, short follow-up, and difficulty attributing changes to AI-enabled systems rather than concurrent organisational interventions.

Synthesis methods

A narrative synthesis was conducted because interventions, settings, technologies, and outcomes were too heterogeneous for pooled estimation. Studies were grouped into command centers, real-time workflow monitoring, operational dashboards, automated decision support, integrated platforms, evaluation approaches, and implementation barriers. Summary judgments focused on deployment maturity, evaluative rigour, degree of automation, and whether AI outputs were descriptive, predictive, or prescriptive.

Results and Discussion

Study selection

The final synthesis included 31 publications addressing smart hospital management, patient-flow coordination, AI-enabled operational prediction, real-time monitoring, dashboards, and automated operational decision support. The PRISMA process narrowed a broad initial search to studies with explicit hospital operations relevance, excluding records focused solely on diagnosis, treatment recommendations, or non-hospital digital health applications [4, 5, 12].

Study characteristics

Included studies were published across 2017–2023 and reflected a mix of health informatics, quality improvement, healthcare engineering, emergency medicine, digital health, and operations research literatures. The evidence base included command-center design and benchmarking studies, RTLS and workflow monitoring studies, process-mining papers, prediction models for admission and length of stay, dashboard-oriented implementation work, and reviews of smart hospital services [1, 5, 6, 10, 11, 13]. Most studies were single-centre or context-specific, and multi-hospital comparative evaluations were uncommon [4, 9, 13].

Command centers: architectures and AI capabilities

Command centers were commonly described as centralized hubs that combine operational dashboards, predictive models, escalation pathways, and multidisciplinary coordination routines. Several studies reported architectures supporting bed prediction, patient-flow visibility, capacity monitoring, and resource coordination across emergency departments, inpatient wards, transfer processes, and discharge planning [1, 2, 13]. The reviewed literature suggests that

command centers are the most mature and visible smart hospital component, although the AI contribution is often embedded within broader systems engineering or operational redesign [1, 3, 4].

Command centers: reported impact

Studies of command centers frequently reported perceived or measured improvements in access, throughput, situational awareness, and operational coordination. However, much of the evidence relied on pre-post designs, implementation narratives, benchmarking surveys, or mixed-method protocols rather than controlled causal evaluation [2, 13, 14]. Several authors noted that command-center impact is difficult to isolate because implementation often coincides with leadership attention, workflow redesign, staffing changes, and broader hospital performance initiatives [3, 4, 15].

Real-time workflow monitoring: sensors and data streams

Real-time workflow monitoring was most often linked to RTLS, patient tracking, Wi-Fi, BLE, sensor data, or similar infrastructure used to measure movement and operational activity. Included studies showed that these systems can provide granular visibility into patient flow, equipment location, staff movement, and outpatient clinic processes [6-8]. At the same time, reviews of RTLS and smart hospital services highlighted uneven implementation, variable data quality, and the need to connect location data to actionable operational decisions [5, 16].

Real-time workflow monitoring: AI/ML methods

AI and analytics methods for workflow monitoring included process mining, sequence analysis, admission prediction, anomaly identification, and bottleneck detection. Process-mining studies demonstrated how event logs can reconstruct patient pathways and reveal operational variation, particularly in emergency and hospital workflow settings [10, 17]. Predictive workflow tools were less frequently deployed in real time, and the literature more often described retrospective discovery or forecasting than closed-loop operational intervention [18-20].

Operational dashboards: design and features

Operational dashboards were typically designed to translate complex hospital data into role-specific views for administrators, bed managers, clinicians, and command-center teams. Reported features included census forecasting, capacity visualization, alert thresholds, escalation displays, patient-flow indicators, and predictive overlays for demand and resource planning [21-23]. The reviewed literature suggests that dashboards increasingly include predictive analytics, but many remain primarily descriptive and depend on human interpretation rather than automated action [23, 24].

Operational dashboards: evidence of effectiveness

Evidence for dashboard effectiveness was generally descriptive, implementation-focused, or based on user experience rather than rigorous assessment of throughput, safety, or cost outcomes. Some studies described operational use of dashboards in pandemic planning, predictive analytics platforms, or quality improvement contexts, but comparative evidence remained limited [9, 21, 24]. Several papers emphasised that dashboards may improve situational awareness only when embedded in governance routines, escalation processes, and workflow redesign [1, 14, 22].

Automated decision support systems: types and scope

Automated decision support systems in the reviewed literature included models for admission prediction, length-of-stay forecasting, patient-bed assignment, discharge planning support, triage, and dynamic capacity planning. Bed-management research and optimization-oriented studies showed how machine learning and operations research can be combined to support patient placement and capacity decisions [12, 25]. Emergency department admission and triage prediction studies also demonstrated operationally relevant use cases, although their deployment as fully integrated management tools was less consistently described [19, 20, 26, 27].

Automated decision support systems: autonomy and oversight

Most decision support systems were advisory rather than autonomous, producing risk scores, forecasts, alerts, or recommendations for human review. Several studies highlighted the feasibility of prediction models for hospital admission, length of stay, or bed requirements, but fewer described governance arrangements for acting on those predictions in live operational settings [11, 28, 29]. This human-in-the-loop pattern reflects appropriate caution, because automated operational decisions can affect patient placement, staff workload, equity, and safety [23, 25, 30].

Component integration and end-to-end smart hospital platforms

Few studies described end-to-end smart hospital platforms integrating command centers, real-time monitoring, dashboards, and automated decision support into a single operational architecture. Smart hospital reviews emphasised the importance of infrastructure integration across EHR, ADT, RTLS, IoT, nurse call, and facility systems, but also noted that implementations often remain fragmented by vendor, department, or use case [5, 6, 16]. The most integrated examples appeared in command-center and predictive-platform studies, where multiple data sources were assembled for situational awareness and operational forecasting [1, 9, 13].

A conceptual maturity framework comparing the core components of smart hospital AI is presented in Table 1.

Table 1. Conceptual Maturity Framework for AI Components in Smart Hospital Management

Component	Functional Role	AI Capability Level	Integration Dependency	Decision Autonomy	Evaluation Maturity	Key Limitation
Command Centers	Centralised coordination and situational awareness	Moderate (embedded predictive tools)	High (requires multi-source data integration)	Low–Moderate (human-led decisions)	Low (mostly observational studies)	Confounding from organisational change
Real-Time Workflow Monitoring	Continuous tracking of patient, staff, and asset movement	Low–Moderate (process mining, anomaly detection)	High (sensor + system integration)	Low (descriptive outputs)	Low (retrospective analyses dominate)	Limited linkage to actionable decisions
Operational Dashboards	Visualization of operational data and forecasts	Moderate (predictive overlays emerging)	Moderate–High	Low (interpretive use)	Very Low (limited outcome validation)	Over-reliance on human interpretation
Automated Decision Support	Prediction and optimisation of operational decisions	High (ML + OR methods)	Very High (requires full data pipeline integration)	Moderate (advisory systems dominate)	Very Low (few real-world deployments)	Governance, safety, and accountability gaps
Integrated Platforms	End-to-end coordination across all components	Potentially High	Extremely High	Moderate–High (theoretical)	Absent (rare empirical evidence)	Fragmentation and interoperability barriers

Evaluation metrics and study designs

Evaluation metrics varied widely across the literature, including length of stay, emergency department waiting, bed occupancy, admission prediction, patient-flow timing, staff experience, operational visibility, and safety-related indicators. Study designs were predominantly observational, retrospective, descriptive, mixed-method, protocol-based, or implementation-focused, with limited use of controlled interrupted time series or randomised designs [2, 11, 13, 23]. This heterogeneity limited direct comparison across studies and prevented meaningful quantitative pooling [4, 10, 12].

Implementation barriers and facilitators

Commonly reported barriers included interoperability limitations, data latency, inconsistent data quality, vendor lock-in, alert fatigue, workflow disruption, unclear accountability, and difficulty demonstrating return on investment. Human factors were also central, because command centers and dashboards require staff trust, training, governance, and role clarity to translate information into action [13, 14, 24]. Facilitators included strong executive sponsorship, multidisciplinary design, integration with existing escalation routines, transparent analytics, and alignment between AI outputs and operational decision rights [1, 3, 9].

Command centers are the flagship, but evidence is thin

Command centers emerged as the flagship manifestation of AI-enabled smart hospital management, combining visibility, coordination, and predictive tools in a recognizable operational hub. However, evidence supporting their impact remains thin because many reports are observational, implementation-oriented, or vulnerable to confounding by concurrent operational improvement programs [1, 2, 13]. The literature therefore supports the plausibility of command-center benefits but not strong causal claims about sustained improvements attributable specifically to AI [3, 4].

Real-time monitoring remains more operational than ai-driven

Real-time workflow monitoring has produced valuable operational visibility, especially through RTLS and patient tracking, but it remains more descriptive than truly AI-driven in many studies. Location and sensor systems can identify movement patterns, dwell times, and equipment availability, yet fewer studies connect these data streams to predictive or prescriptive interventions [6-8]. Process-mining work provides a bridge toward AI-enabled workflow intelligence, but much of it remains retrospective rather than continuously embedded in hospital operations [10, 17].

Dashboards are proliferating without standardised impact evaluation

Dashboards are proliferating as hospitals seek to convert operational data into timely management information, but standardised evaluation is lacking. Several studies described dashboards or predictive analytics platforms for command centers, pandemic planning, or care-quality monitoring, yet outcomes were often context-specific and difficult to compare [9, 21, 24]. Poorly designed dashboards may overwhelm users or encourage reactive management unless visualisation, thresholds, accountability, and escalation logic are carefully aligned [21, 23].

Automated decision support is the least deployed, highest-stakes component

Automated decision support appeared to be the least fully deployed but potentially highest-stakes smart hospital component. Prediction and optimization studies demonstrated possible applications in bed assignment, admission forecasting, length-of-stay prediction, triage, and capacity planning, but these models were not consistently embedded into governed operational workflows [12, 19, 25, 27]. Because such systems can influence patient placement, staffing, and access to resources, the literature points to unresolved questions about safety, fairness, explainability, and accountability [20, 23, 30].

The integration challenge

The central challenge for smart hospital AI is integration rather than isolated model performance. Truly smart operations require continuous links among command centers, monitoring systems, dashboards, decision support, EHR data, ADT

feeds, RTLS infrastructure, and human escalation processes [5, 6, 16]. The reviewed studies suggest that current implementations often remain siloed, which limits their ability to provide holistic, real-time situational awareness and coordinated operational response [1, 9, 13].

The integrated architecture of AI-enabled smart hospital management systems is illustrated in **Figure 2**.

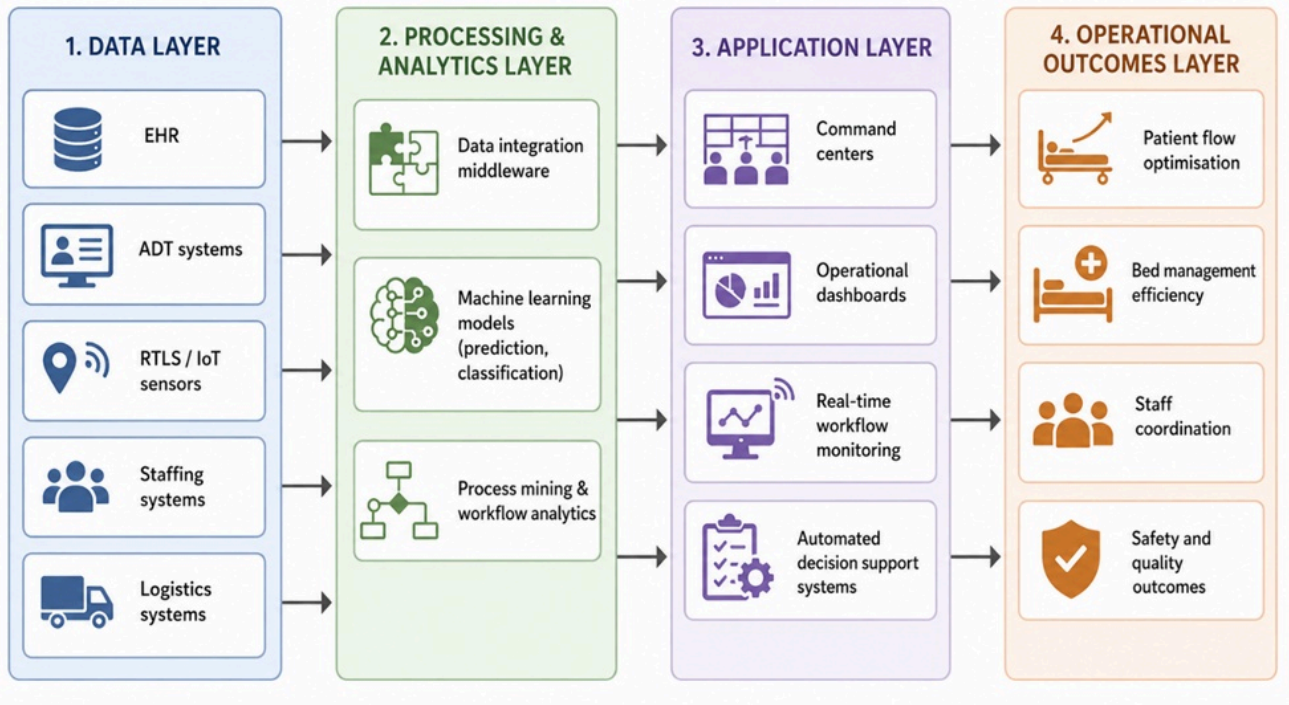


Figure 2. Hierarchical Architecture of AI-Enabled Smart Hospital Management Systems

Human Factors and Organisational Readiness

Human factors and organisational readiness were recurring determinants of whether AI-enabled operational tools were likely to be useful. Command centers require trust in data, clear decision rights, staff training, and leadership support, while dashboards require careful design to avoid alert fatigue or misinterpretation [13, 14, 24]. Several studies implied that smart hospital AI should be treated as socio-technical transformation rather than technology installation alone [1, 3, 15].

The socio-technical dependencies and potential failure points of smart hospital AI systems are analytically mapped in **Table 2**.

Table 2. Analytical Mapping of Socio-Technical Dependencies and Failure Points in Smart Hospital AI Implementation

System Layer	Technical Dependency	Human/Organisational Dependency	Failure Mode	Downstream Impact	Mitigation Strategy
Data Acquisition	Accurate, real-time EHR/ADT/RTLS feeds	Data governance and data entry compliance	Data latency or inconsistency	Incorrect predictions and delayed decisions	Data validation pipelines and real-time monitoring

Data Integration	Interoperable middleware and APIs	IT governance and vendor coordination	Fragmented data silos	Loss of system-wide visibility	Standardised interoperability frameworks
Analytics Models	Validated ML and optimisation models	Trust in model outputs	Model bias or poor generalisation	Unsafe or inequitable decisions	Local validation and explainability tools
Interface Layer (Dashboards)	Usable and interpretable visualisation systems	User training and cognitive load management	Misinterpretation or alert fatigue	Ineffective or delayed responses	Human-centred design and threshold tuning
Decision Support	Reliable recommendation systems	Clear decision rights and accountability	Over-reliance or under-utilisation	Inconsistent operational actions	Governance protocols and escalation pathways
Organisational Integration	Workflow alignment and escalation routines	Leadership support and cultural readiness	Resistance to adoption	System underutilisation	Change management and stakeholder engagement
Evaluation Layer	Robust outcome measurement systems	Commitment to rigorous evaluation	Lack of causal evidence	Misleading claims of effectiveness	Prospective and controlled study designs

Towards evaluative rigour

The field needs to move from promising implementation narratives toward stronger evaluation designs. Reviews and methodological papers highlighted recurring weaknesses in prediction validation, uncontrolled evaluations, selective reporting, and insufficient attention to implementation context [4, 11, 23]. Future studies should use prospective designs, controlled comparisons where feasible, interrupted time-series analyses, and transparent reporting of data sources, governance, and workflow integration [2, 10, 12].

Limitations

Review limitations

This review was limited by the use of English-language peer-reviewed publications and by reliance on a predefined reference set focused on the most relevant literature from 2017 to 2023. Publication bias is possible because successful command-center and dashboard implementations may be more likely to be reported than unsuccessful or abandoned projects [4, 13, 15]. Heterogeneity in intervention type, hospital context, AI maturity, and outcome measurement prevented meta-analysis and required narrative synthesis [10-12].

Evidence base limitations

The evidence base itself was limited by single-centre studies, retrospective analyses, implementation reports, protocol papers, and prediction models that were not always evaluated as deployed operational systems. Several papers reported promising capabilities for forecasting, triage, bed planning, or real-time analytics, but fewer demonstrated sustained use across departments with independent evaluation [9, 26, 28, 31]. Vendor involvement, local workflow redesign, and

concurrent organisational initiatives also make it difficult to distinguish the effects of AI from broader management change [1, 9, 14].

Comparison with prior reviews

Prior reviews have usually addressed narrower domains such as command centers, RTLS, process mining, smart hospital services, inpatient bed management, or length-of-stay prediction. For example, command-center and capacity-management reviews mapped emerging centralized hospital operations models, while RTLS and process-mining reviews focused on workflow visibility and pathway discovery rather than full operational integration [4, 6, 10]. Similarly, reviews of smart hospital services and inpatient bed management described important infrastructure and modelling issues but did not jointly assess command centers, real-time monitoring, dashboards, and automated decision support as an integrated AI-enabled management architecture [5, 11, 12].

This review extends prior work by organising the evidence around the operational architecture of smart hospital AI. Instead of treating dashboards, bed prediction, RTLS, workflow mining, and command centers as isolated topics, the synthesis examined how these components contribute to situational awareness, forecasting, coordination, and operational action [1, 7, 9, 13]. This broader framing shows that the field has many functional components but relatively few examples of mature integration across data streams, governance processes, and decision rights [5, 16, 25].

A distinctive contribution of this review is its emphasis on the evaluation gap that threatens the credibility of the smart hospital movement. Several included studies described promising prediction models, dashboards, command-center functions, or workflow-monitoring tools, but rigorous prospective evidence linking these systems to sustained operational improvement was limited [2, 19, 21, 27]. This pattern aligns with broader concerns that predictive analytics in healthcare must demonstrate real-world impact, not only technical feasibility or face-valid operational relevance [23, 30].

Recommendations

Researchers should standardise outcome measures for smart hospital AI, including length of stay, boarding time, bed turnover, transfer delay, staff workload, alert burden, patient safety, and financial sustainability, and they should prioritise prospective controlled evaluations or interrupted time-series designs when randomisation is not feasible [4, 11, 23]. Hospital leaders should invest in data integration middleware, interoperable EHR and ADT pipelines, RTLS governance, and multidisciplinary escalation routines before deploying component-specific AI tools, because isolated dashboards or prediction models are unlikely to transform operations without organisational readiness [1, 5, 6, 14]. Vendors should provide open APIs, transparent model documentation, auditable alert logic, and explainable recommendations that allow hospitals to evaluate safety, fairness, and local validity before operational decisions are influenced by automation [9, 20, 25]. Journals should require detailed reporting of implementation context, data provenance, model validation, human factors, workflow integration, governance arrangements, and financial assumptions in all smart hospital AI studies [2, 13, 24].

Research gaps

The field urgently needs prospective, controlled studies that distinguish the independent contribution of AI-enabled smart hospital tools from concurrent leadership attention, staffing changes, workflow redesign, and quality-improvement initiatives [2-4]. There is a major gap in evidence on multi-component integration, particularly how command centers, real-time workflow monitoring, predictive dashboards, and automated decision support interact when implemented together across emergency departments, inpatient wards, operating rooms, discharge teams, and logistics services [1, 5, 9, 16]. Human-AI interaction in operational decision-making remains underexplored, including how managers interpret predictions, when staff override automated recommendations, and how accountability is assigned when AI-supported patient placement or staffing decisions have adverse consequences [23, 25, 27]. Research on fairness, equity, long-term cost-effectiveness, vendor dependence, cybersecurity, and sustainability is also limited, despite the likelihood that

automated resource allocation could affect access, waiting times, and workload distribution across patient groups and clinical teams [13, 20, 30].

Implications

For practice, current evidence suggests that smart hospital AI should be implemented incrementally, with local validation, staged deployment, and continuous monitoring rather than wholesale adoption based on vendor claims or isolated success stories [4, 9, 13]. For policy, accreditation bodies, health system regulators, and professional organisations should begin defining standards for AI-supported operational decisions, especially when predictive systems influence bed placement, triage escalation, staffing adjustment, discharge prioritisation, or interfacility transfer [19, 20, 26, 27]. For research, the priority should shift from building additional models toward demonstrating that deployed systems improve operational efficiency, patient safety, staff experience, and equity in real hospitals without creating new risks, alert burden, or opaque decision pathways [23, 29, 31]. For health system leadership, the review implies that AI-enabled command centers and dashboards should be treated as socio-technical infrastructure requiring governance, training, interoperability, and accountability rather than as standalone digital products [1, 14, 24].

Conclusion

AI in smart hospital management expanded rapidly between 2017 and 2023, but the evidence base remains dominated by single-component, low-rigour studies. The literature demonstrates substantial interest in using AI to improve hospital flow, capacity management, and operational visibility, but it does not yet establish strong causal evidence of sustained transformation.

Command centers and dashboards are the most prevalent components of current smart hospital AI. Real-time workflow monitoring and automated decision support are less developed, less integrated, and less consistently evaluated in live operational settings.

The absence of integrated, multi-component evaluations is the central weakness of the field. A second major weakness is the lack of controlled designs capable of separating the effect of AI from broader organisational change, management attention, and workflow redesign.

A new phase of implementation science is required to validate whether smart hospital AI can deliver its promised transformation of hospital operations. Future work must demonstrate not only that these systems can predict, display, or recommend operational actions, but also that they improve care delivery safely, equitably, and sustainably.

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