

An umbrella review of facilitators and barriers to the adoption, spread and sustainability of AI solutions within hospital settings

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Abstract

There is a growing use of artificial intelligence (AI) in healthcare settings, but challenges exist with AI adoption and its long-term use. This umbrella review funded by the NIHR (NIHR205439), aimed to identify the facilitators and barriers of AI implementation within hospitals and was registered on PROSPERO. Five databases (MEDLINE, HMIC, CINAHL Plus, Web of Science and Cochrane Reviews) were searched in January 2025 and re-run in February 2026, 1184 articles were screened, with 20 included. The inclusion criteria encompassed reviews implementing AI within hospital settings. The quality of the data were assessed using the ROBIS checklist and data were synthesised using the NASSS (Nonadoption, Abandonment, and challenges to the Scale-up, Spread, and Sustainability) framework. We found AI implementation was affected by: whether an AI solution as an intervention had been externally validated to ensure generalisability across different settings; evidence that the AI solution brings measurable gains; the level of trust in and understanding of the AI solution among hospital staff; the budgets and resources available to onboard the AI solution, train staff, and maintain the solution; the need for national policies on funding and regulating AI solutions. These factors affected the adoption, spread, scalability, and sustainability of AI implementation and should be considered for future implementation.

Keywords

health services, systematic reviews, implementation science, artificial intelligence, hospital

Introduction

There is a growing use of artificial intelligence (AI) in healthcare settings,^{1–3} that offers potential economic advantages, medical service enhancement, and optimisation of resources within hospitals.^{1,2} AI refers to computational systems designed to perform tasks that typically require human intelligence, such as problem solving, pattern recognition, decision making, and learning,^{2,4} based on algorithms. A key subset of AI is machine learning (ML), which involves training algorithms on large datasets to identify patterns and make predictions about new, unseen data.⁴ These algorithms can improve their performance over time as they are exposed to more data, without needing to be explicitly reprogrammed.^{4,5} However, within healthcare, machine learning models are usually fixed prior to implementation for patient safety, so they don't undergo changes without human approval to prevent errors going unnoticed.^{6–8} Deep learning (DL) is a more advanced form of machine learning that uses

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layered structures of neural networks to process large and complex types of data, including images, speech, and text.^{4,5}

Despite AI's potential and similarly to other healthcare technologies, its actual adoption and long-term use within the complex environment of healthcare can be impeded due to factors within the technology, the individuals using the technology, the healthcare organisation rolling out the technology and wider societal factors.^{9–14} Existing research, including the reviews by Hassan et al. and Ahmed et al., have highlighted numerous barriers and facilitators to AI implementation in healthcare,^{2,15} such as limited transparency of AI solutions; algorithm bias; integration within existing technological infrastructure; the financial costs; and regulatory and legal requirements. Reviews have also focused on the barriers and facilitators of AI implementation within specific healthcare contexts such as acute care¹⁶ and nursing.¹⁷ Although these reviews highlight how AI integration into healthcare is influenced by various factors in specific clinical areas, no umbrella review has yet explored cross cutting factors across clinical settings.

This review was guided by the Nonadoption, Abandonment, and challenges to the Scale-up, Spread, and Sustainability (NASSS) framework, which has been developed for use in evaluating the implementation of technology-based interventions in complex healthcare settings.^{10–14} The NASSS framework consists of seven domains that can shed light on factors that may lead to or prevent the non-adoption or the abandonment of an AI-based intervention, it can also demonstrate factors that may impact the scale-up of the use of the intervention at a local hospital, the spread of the intervention to other hospitals, and then the sustainability of the intervention across hospitals in terms of its ability to be used in the long-term.^{11,13,14} The aim of this umbrella review is to identify the factors acting as barriers and facilitators to implementing AI in hospital settings using NASSS as a conceptual framework.

Methods

This umbrella review was developed in accordance with the Preferred Reporting Items for Overviews of Reviews

(PRIOR) guidelines outlined by Gates et al. (2022).¹⁸ The protocol for the review was registered with PROSPERO (CRD 42025638087).¹⁹

Search strategy

A scoping search of the existing literature was conducted on Google Scholar by using the search terms 'Artificial intelligence' AND 'hospital' AND 'review'. Researchers identified key terms used in previously published reviews on this topic. Following this the search terms: 'Artificial Intelligence or Machine learning or Deep learning' AND 'Hospital' AND 'Systematic review' were agreed among the researchers who have experience conducting reviews and research experience in the field of artificial intelligence. The searches were implemented across five databases: MEDLINE, CINAHL Plus, HMIC, Cochrane Reviews, and Web of Science in January 2025 with no limitations on the date of publication, and then re-run in February 2026. The detailed search criteria can be found in [Supplement 1](#).

Inclusion and exclusion criteria

The eligibility criteria used for the review can be found in [Table 1](#). The design of reviews that could be included were limited to systematic reviews, meta-synthesis or meta-analyses, however there were no limitations on the types of study design that could be included within the reviews, so quantitative, qualitative, and mixed method study designs were all relevant. Hospital settings were the only type of clinical setting included, where interventions had to take place either in the physical hospital building, or interventions with an at-home component so long as the technology was also implemented within the hospital and by hospital staff. AI and its subset technologies were also part of the inclusion criteria. There were no exclusions based on the country of the studies within the reviews. Publications were limited to those that shared the barriers and facilitators to implementing AI in the hospital setting. Reviews not mentioning AI, those conducted outside hospital

Table 1. Inclusion criteria.

Inclusion	Exclusion
Use of artificial intelligence (AI) or subset techniques. • AI as an overarching system that processes large bodies of data through a subset of analytical techniques. • Subset of analytical techniques such as machine learning, natural language processing, deep learning, etc.	No mention of AI or subset techniques
Services, interventions or approaches conducted in the hospital setting (including wearable or remote approaches so long as the AI solution is used within the hospital and by hospital staff).	Not a hospital setting (e.g., dentist or GP).
Systematic review, meta-synthesis, meta-analysis.	Not a review of publications (e.g., single empirical study) or non-systematic review (e.g., scoping review or integrative review).
Implementation of AI; or barriers or facilitators to AI implementation.	

*No limitations on study designs included in the reviews; country or language of publication; date of publication.

environments (e.g., dental practices, primary care clinics), or articles that were single empirical studies rather than reviews were excluded.

Article selection

Once searches were retrieved from the scientific databases, the results were de-duplicated using Endnote and then imported into the software Rayyan for title and abstract screening.²⁰ Researchers (S.E.C., S.M., A.E.S., Y.Z., Y.B.M.) conducted screening of the same 25% of title and abstracts. The researchers identified any discrepancies and had discussions to reconfirm the teams understanding of the eligibility criteria. Once confident with their understanding, two researchers (S.E.C., S.M.) then split and independently screened the remaining publications. A similar process was initiated with full text screening, the researchers conducted screening on the same 25% of full texts (S.E.C., S.M., A.E.S., Y.Z., Y.B.M.), followed by team discussions to identify discrepancies and build confidence for three researchers (S.E.C., S.M., Y.B.M.) to split and independently screen the remaining full texts.

Data extraction and synthesis

A Microsoft Excel data extraction form was developed using the domains of the Nonadoption, Abandonment, Scale-Up, Spread, and Sustainability (NASSS) framework.²¹ The descriptive data extracted included: the number of studies within the reviews; the type of AI or machine-learning approaches used; the clinical setting or condition the interventions were being used in; and the perspectives being collected. Data was deductively extracted from the results sections of the publications if they related to one of the 7 NASSS domains as a best-fit framework: the condition; the technology; the value proposition; the adopter system; the organisation; the wider context; and how domains interact with each other and adapt (see Table 3 for further details about these domains). Where needed the researchers referred to some of the original publications within the reviews for further detail. The data extraction form was piloted among the research team (S.E.C., S.M., A.E.S., Y.Z., Y.B.M.) who extracted data from the same 25% of included publications to build confidence and ensure alignment, three researchers (S.E.C., S.M., Y.B.M.) then independently extracted data from the remaining publications. The content from the data extraction form was further categorised into barriers or facilitators within each of the domains. The researchers then used narrative synthesis to interpret the data from the data extraction form.

Critical appraisal

The ROBIS tool is a critical appraisal tool for assessing the risk of bias in systematic reviews.³⁹ ROBIS was used to

evaluate the quality of the reviews and the different study designs of their included literature (qualitative, quantitative, and mixed methods studies). The quality assessment was conducted by three researchers, one (S.E.C.) conducting the initial quality appraisal, and two additional researchers (S.M., Y.B.M.) cross-checking the decisions.

Results

Review characteristics

The search was performed across five databases, yielding 1554 records. After duplicates were removed, 1184 records remained for title and abstract screening. After the screening, 260 articles remained and underwent full text screening. As a result of screening, 18 articles were selected for data extraction. An additional two articles were included from screening the first 100 results on Google scholar during the scoping process. An overview of the results from the screening process can be found in Figure 1, and the included items can be found in Supplement 2.

Table 2 highlights the characteristics of the 20 systematic reviews which were published between 2023 and 2026, apart from one review published in 2017. Most reviews focused on AI, machine learning or deep learning-based approaches broadly, and three reviews focused specifically on generative AI and large language models.^{17,24,28} The reviews varied in size, whereby the reviews synthesised between five to 59 individual research studies. The reviews collated information from publications that were empirical studies collecting perspectives from patients and hospital staff; publications that included perspectives from hospital staff who were the authors of publications evaluating the use of AI; or were publications collating recommendations on the use of AI. Most reviews cited the geographical locations of the included literature, and this is shown in Table 2. A global perspective was represented across the reviews spanning Africa, Asia, Europe, North America, South America and Oceania. However, there were some reviews that did not cite this information. After checking the individual studies included in each review, the research team identified that 13 of the reviews contained some of the same studies (as shown in Supplement 3). We therefore refrained from quantifying the frequencies of these factors acting as barriers or facilitators, and instead have described the different types of factors.

The ROBIS assessments can be found in Table 2 with further detail in Supplement 4. Nine reviews had low concerns for risk of bias across all four domains of the tool, with caveats such as some reviews not having clear synthesis of findings, or not having dual approaches for screening, extraction, or appraisal, or no alternative modes to database searching.^{22–24,28,32–34,36,37} Six publications had one domain with a high concern for risk of bias, because of having a combination of the issues mentioned in the

previous sentence, and lacking detail on eligibility criteria, on search terms or on quality appraisal.^{15,25,26,29,30,35} Five publications had two domains with a high concern for a risk of bias, due to having many combinations of the issues discussed so far,^{16,17,27,31,38} we therefore recommend caution when interpreting these findings.

The reported facilitators and barriers to AI implementation aligned to the NASSS framework

Across the reviews there were 32 factors cited as barriers and 30 factors cited as facilitators to the adoption, non-abandonment, scale-up, spread and sustainability of AI or machine-learning approaches in hospitals. These factors have been summarised in Table 3 against the seven domains of the NASSS framework.¹¹ Most barriers and enablers were grouped under the technology domain.

Domain 1: The condition. The first domain of the NASSS framework focusses on the clinical characteristics of the medical condition for which a technology is introduced. Most of the reviews focussed broadly on the clinical setting that AI was used in, as opposed to its use with specific conditions. However, three reviews focussed specifically on the use of AI in patients with sepsis,²⁶ experiencing deterioration,²³ or patients experiencing hypoxic-ischemic encephalopathy.³⁶ None of the reviews specifically addressed the extent to which characteristics of specific conditions may impede or facilitate AI implementation. However, the 2023 review by van der Vegt et al. discussed how there are various definitions for sepsis and its different stages. The authors flagged the definition would need to be narrowed down in advance of implementing a machine-learning algorithm (MLA) as it would impact the specificity and sensitivity of the MLA's prediction. Depending on which outcome definition was used (e.g., initial

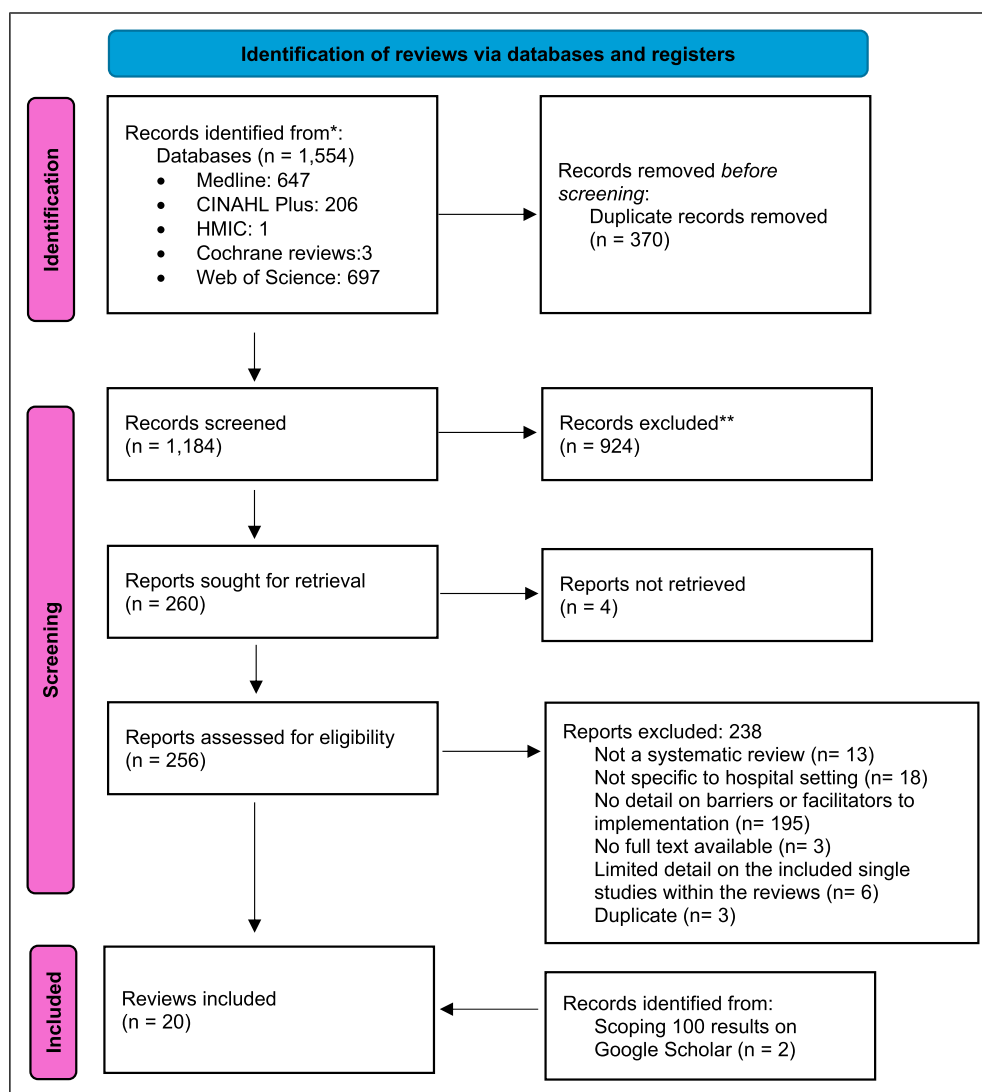


Figure 1. PRISMA flow diagram.⁴⁰

Table 2. Review characteristics.

Author(s)	Year	Type of review	Aim	Number of studies	Type of AI	Type of clinical setting, condition and geographic location	Perspectives captured	ROBIS overview
Ahmed et al. ¹⁵	2023	Systematic review	To systematically classify and discuss key obstacles slowing the integration of AI technologies into clinical pathways and organisational processes.	59	ML + DL	Setting: Any healthcare Condition: N/A Location: Not specified (on review of included literature it provides a global perspective)	Empirical studies collecting hospital staff's views. Publications collating recommendations on the use of AI.	One of four domains with high risk of bias.
Bellini et al. ¹⁶	2024	Systematic review	To examine the recent use of artificial intelligence, particularly machine learning, in the management of operating rooms.	22	ML + DL	Setting: Operating rooms Conditions: N/A Location: USA, Colombia, Australia, Israel, Singapore, China, Taiwan, Iran, New Zealand, Canada	Publications collating recommendations on the use of AI	Two of four domains with high risk of bias.
Kucukkaya et al. ¹⁷	2024	Systematic review	To evaluate ChatGPT's utility in ICU nursing education and practices, assessing its effectiveness and develop strategic recommendations for its future incorporation into critical care.	5	Generative AI (AI chatbots)	Setting: Intensive care Conditions: N/A Location: Israel, Saudi Arabia, USA, Brazil	Based on perspectives from hospital staff who authored the included publications evaluating AI	Two of four domains with high risk of bias.
van der Vegt et al. (Scott, Dermawan et al.) ²⁶	2023	Systematic review	To retrieve and critically appraise studies deploying AI sepsis-prediction models, extract implementation barriers/enablers, and map them to the SALIENT clinical-AI implementation framework.	30	ML + DL	Setting: ICU and non-ICU hospital settings Condition: Sepsis Location: USA, Brazil	Empirical studies collecting hospital staff views Publications collating recommendations on the use of AI	One of four domains with a high risk of bias.
Kamel Rahimi et al. ²²	2024	Systematic review	(i) Identify real-world enablers and barriers to AI implementation in hospital settings; (ii) map those factors onto a "three-horizon" digital-transformation framework for building a learning health system.	26	ML + DL	Setting: Hospital Condition: N/A Location: UK, Sweden, USA, Netherlands, Germany, Canada, China, Austria, Japan	Empirical studies collecting hospital staff views Publications collating recommendations on the use of AI	Low risk of bias across all four domains.

(continued)

Table 2. (continued)

Author(s)	Year	Type of review	Aim	Number of studies	Type of AI	Type of clinical setting, condition and geographic location	Perspectives captured	ROBIS overview
Baig et al. ³¹	2017	Systematic review	To analyse barriers and challenges of wearable patient monitoring (WPM) solutions adopted by clinicians in acute, as well as in community, care settings.	20	ML	Setting: Acute care (and community care) Conditions: N/A Location: Not specified (on review of included literature it provides a global perspective)	Based on perspectives from hospital staff who authored some of the included publications evaluating AI	Two of four domains with high risk of bias.
van der Vegt et al. (Campbell, Mitchell et al.) ²³	2024	Systematic review	To identify factors influencing implementation of machine learning algorithms (MLAs) that predict clinical deterioration in hospitalized adult patients and relate these to a validated implementation framework.	37	ML + DL	Setting: Hospital Condition: Patient deterioration Location: USA, Australia, Korea, Canada, Singapore	Based on perspectives from hospital staff who authored some of the included publications evaluating AI	Low risk of bias across all four domains.
Tan & Mills ²⁷	2024	Systematic review	What AI strategies apply to emergency departments? Moreover, what challenges and opportunities are involved in using AI equipment in emergency departments?	36	ML + DL	Setting: Emergency departments Conditions: N/A Location: Not specified (on review of included literature it provides a global perspective)	Based on perspectives from hospital staff who authored some of the included publications evaluating AI	Two of four domains with high risk of bias.
Ouanes & Farhah ³⁸	2024	Systematic review	To identify the use and application of AI in clinical decision support systems, including its impact on patient outcomes, clinical practice, and healthcare costs.	26	ML + DL	Setting: Any healthcare Condition: N/A Location: Not specified (on review of included literature it provides a global perspective)	Empirical studies collecting hospital staff views	Two of four domains with high risk of bias.
Rajeshwari et al. ³⁶	2025	Systematic review	To identify challenges related to limited dataset sizes, model applicability across diverse populations, and integration into clinical practice.	5	DL	Setting: Hospital - MRI Condition: Hypoxic-ischemic encephalopathy Location: USA, China, Netherlands, Croatia	Based on perspectives from hospital staff who authored the included publications evaluating AI	Low risk of bias across all four domains.

(continued)

Table 2. (continued)

Author(s)	Year	Type of review	Aim	Number of studies	Type of AI	Type of clinical setting, condition and geographic location	Perspectives captured	ROBIS overview
Abdallah et al. ³²	2025	Systematic review	To evaluate the body of research on the current application of AI in PICUs, as well as the potential for bias. To highlight key challenges in AI adoption, including data scarcity, model validation, and the need for standardized evaluation metrics.	32	ML	Setting: Paediatric intensive care Condition: N/A Location: Not specified (on review of included literature it provides a global perspective)	Based on perspectives from hospital staff who authored the included publications evaluating AI	Low risk of bias across all four domains.
Amin et al. ³³	2026	Systematic review	To explore the ethical dimensions of AI-driven patient monitoring in critical care nursing, focusing on autonomy, privacy, accountability and equity as reported by ICU nurses and patients.	6	ML + DL	Setting: Critical care nursing Condition: N/A Location: Egypt, Saudi Arabia, Jordan, USA, Canada	Empirical studies collecting hospital staff views Based on perspectives from hospital staff who authored the included publications evaluating AI	Low risk of bias across all four domains.
Daccache et al. ²⁸	2025	Systematic review	To describe the integration of LLMs in the field by showcasing and categorizing their current applications, assessing their performance in patient care, and reviewing application-specific ethical and practical challenges in deployment.	22	Large language models	Setting: Anesthesiology and critical care Condition: N/A Location: USA, Switzerland, Korea, Colombia, France, India, Israel, China, Germany, Saudi Arabia, Turkey, Japan	Empirical studies collecting hospital staff and patient views	Low risk of bias across all four domains.
El Arab & Al Moosa ³⁴	2025	Systematic review	To critically evaluate and synthesize the current evidence on the validation and clinical impact of AI and ML-based models for triage and risk stratification in emergency departments—encompassing both general and disease-specific applications—with an emphasis on performance metrics, workflow feasibility, and patient outcomes.	26	ML + DL	Setting: Emergency departments Condition: N/A Location: North America, Asia, Europe, Africa, Middle East, South America	Based on perspectives from hospital staff who authored the included publications evaluating AI	Low risk of bias across all four domains.

(continued)

Table 2. (continued)

Author(s)	Year	Type of review	Aim	Number of studies	Type of AI	Type of clinical setting, condition and geographic location	Perspectives captured	ROBIS overview
Joo et al. ³⁷	2025	Systematic review	To conduct a systematic literature review and thematic synthesis of qualitative studies to identify common issues surrounding the adoption of AI in nursing care.	9	AI + ML	Setting: Nursing within hospitals Condition: N/A Location: USA, Bangladesh, Finland, Egypt and China	Empirical studies collecting hospital staff views	Low risk of bias across all four domains.
Kwon & Kim ²⁴	2026	Systematic review	This systematic review aims to (1) examine the specific aspects of nursing decision-making impacted by generative AI, (2) identify the types of generative AI technologies being used or studied in nursing practice, (3) evaluate the reported benefits and positive impacts on nursing decision-making, (4) identify the challenges, limitations, and risks associated with generative AI use, and (5) discuss implications for nursing practice, education, and policy.	23	Generative AI	Setting: Nursing across healthcare including hospitals Condition: N/A Location: Israel, Hong Kong, South Korea, China, USA, Australia, Taiwan, multi-national	Empirical studies collecting hospital staff views	Low risk of bias across all four domains.
Maimaitiali et al. ²⁵	2025	Systematic review	What empirical evidence supports each layer of the proposed 5-layer architecture? How do the interrelationships among layers reveal strengths and gaps in hospital-level AI research?	29	AI + ML	Setting: Hospital Condition: N/A Location: USA, France, China, UK, India, Korea, Germany, Uganda, Italy, Switzerland, Netherlands	Empirical studies collecting hospital staff views Based on perspectives from hospital staff who authored the included publications evaluating AI	One of four domains with a high risk of bias.
Nacu et al. ³⁵	2025	Systematic review	This systematic review explores the evolving landscape of ethical dilemmas and legal responsibilities in hospital-based patient care, with particular attention to how they intersect with institutional safety.	40	AI + ML	Setting: Hospital Condition: N/A Location: Uganda, China, Indonesia, USA, Uzbekistan, Germany, Canada, UK, France, Italy, Ukraine, Saudi Arabia, India, Switzerland, Poland, Africa, international	Publications collating recommendations on the use of AI	One of four domains with a high risk of bias.

(continued)

Table 2. (continued)

Author(s)	Year	Type of review	Aim	Number of studies	Type of AI	Type of clinical setting, condition and geographic location	Perspectives captured	ROBIS overview
Roychowdhury et al. ²⁹	2025	Systematic review	To investigate the effectiveness of Explainable AI (XAI) in machine learning (ML)-based clinical decision support systems (CDSS) using non-imaging data, focusing on explanation quality, clinical decision-making, user trust, and usability.	22	ML + DL	Setting: Clinical decision support systems across healthcare including hospitals Condition: N/A Location: Not specified (on review of included literature it provides a global perspective)	Empirical studies collecting hospital staff and patient views	One of four domains with a high risk of bias.
Tudor et al. ³⁰	2025	Systematic review	To analyze the current AI research landscape for predicting clinical outcomes and length of stay in the NICU and (2) to explore the benefits and challenges of using AI in the NICU for these predictions.	24	ML + DL	Setting: Neonatal intensive care units Condition: N/A Location: USA, Austria, Taiwan, Argentina, China, Denmark, Iran, Italy, Tanzania	Based on perspectives from hospital staff who authored the included publications evaluating AI	One of four domains with a high risk of bias.

Abbreviations: AI – Artificial Intelligence; ML – Machine Learning; DL – Deep Learning.

*RoB – Risk of bias.

Table 3. Summary of the facilitators and barriers within the NASSS domains.

NASSS Domain	Barriers	Facilitators
Domain 1: Condition Clinical characteristics, co-morbidities, and socio-cultural aspects of the condition.	N/A	N/A
Domain 2: Technology The material and technical features of the technology. The knowledge generated or made visible by technology. The knowledge and support needed to use the technology. The sustainability of the technology.	1. Lack of robust technological infrastructure^{15,22–25} 2. Challenges integrating the AI into the tools staff already use¹⁵ 3. Concerns around the data being fed into AI platforms^{15,17,22,23,26–30} 4. Substantial time to enter and process data^{22,23,31} 5. Lack of interpretability and transparency of AI models^{15,25,29,30,32–35} 6. False positive alerts and alert fatigue^{15,22,23,26} 7. Inaccurate outputs adding burden to users workflow²⁶ 8. Limited efficacy of AI outputs²² 9. Lack of external validation^{22,23,29,30,32,36} 10. Poor model performance due to model drift and underfitting^{22,25} 11. Models don't capture if users have acted on the model recommendation²⁶ 12. AI systems that perpetuate biases^{15,23,28,33,36}	1. AI that integrates within existing computational resources and tools²² 2. AI platform secure for hospital IT²² 3. AI tool has a user-friendly interface^{22,29,30} 4. Reduce false alarms²³ 5. External validation^{22,23} 6. Ensure model drift is captured^{22,25,26} 7. Models that are interpretable and transparent^{29,36}
Domain 3: Value proposition Developer's business case for the technology. Desirability, efficacy, safety, and cost effectiveness.	13. Limited empirical evidence of the rigorous evaluation or the added value of AI^{15,16,26,29} 14. Lack of clarity regarding the relevance of AI solutions²² 15. Challenges evaluating the model without informatic institutions²²	8. Evidence of measurable benefits in health outcomes, workload and costs^{22,34} 9. Evaluate the roll-out of AI^{22,23,26} 10. Research studies showing impact of AI^{22,23} 11. Tool that seems easy to use^{33,37}
Domain 4: Adopter system Changes in staff roles and practices. Adoption and acceptance by patients, and expectations of patients. Assumptions that lay caregivers will be available.	16. Lack of trust in AI^{15,16,22–26,28,29,33,38} 17. Limited training and education on AI^{15,16,23,24,26,27,33,38} 18. Fears of AI undermining autonomy and staff losing skills^{15,24,29,33,37,38} 19. Fears of job displacement¹⁵ 20. Lack of clarity whether a clinician will be liable for acting on AI's recommendation^{15,24,35,38} 21. Not engaging end-users^{15,16} 22. Concerns that data will not be kept private or secure^{33,37}	12. Witnessing AI solutions make correct predictions^{23,26} 13. Training and guidance on AI^{22,23,26,38} 14. Patients consent for data usage in AI systems^{15,35} 15. Balancing the use of AI with clinician autonomy^{26,33,37,38} 16. Co-designing the AI solutions with staff and patients^{22,23,26,29,38} 17. Raising awareness among staff and advocates for the tool^{22,23,25,26} 18. Multi-disciplinary team to promote, use, and track the tool^{22,23,25,26} 19. A professional helping roll out of the tools with hospital staff^{22,26}

(continued)

Table 3. (continued)

NASSS Domain	Barriers	Facilitators
Domain 5: The organisation	23. The organisational cost of AI ^{15,22,23,25–27}	20. Funding for AI ²²
Organisation's capacity (to embrace any service-level innovation) and readiness (for a specific technology).	24. Organisational culture and resource constraints ²²	21. Organisational culture that is receptive to digital health ²²
Adoption decision, typically a board-level decision to allocate a budget line to support a particular technology.	25. Challenges integrating AI into workflows ^{15,22,24,25,27,29,37}	22. Buy-in from senior leadership ^{22,23,26}
Established work routines will be disrupted or made too brittle by the new technology.	26. Limited implementation plans or governance policies ^{22,24,25,35}	23. Non-disruptive and staggered integration of AI within and across sites ^{22,23,26,34}
Worked involved in implementation, and who will do it.		24. Implementation plans ^{22,32,33}
Domain 6: The wider context	27. Lack of national governance of ethical and legal considerations for AI ^{15,16,25,35,37}	25. Standardisation in AI roll-out ²²
The political, economic, regulatory, and sociocultural context.	28. Lack of an agreed framework for the evaluation AI models ^{15,29}	26. National initiatives that support the implementation of AI ^{22,25,30}
	29. High cost of AI for health systems ^{15,22}	27. Regulatory approval on whether AI is a medical device ²⁶
Domain 7: Interactions & adaptation over time	30. Limited continuous regulation of algorithms ¹⁵	28. Improvement cycles based on live feedback ^{22,23,26}
Medium- and long-term feasibility of continuing to adapt the technology and the program.	31. Minimal user feedback prohibits continuous improvement ^{23,29}	29. AI models that anticipate future shifts ²²
Organisation's resilience to handling critical events and adapting to unforeseen eventualities.	32. Costs of ongoing maintenance and training ^{25,26}	30. Open-source pipelines allows for new algorithms ²²

inflammatory process vs multi-organ dysfunction) the algorithm could either predict the likelihood of developing sepsis or diagnose current sepsis.²⁶

Domain 2: The technology. Numerous publications reported factors related to technology that could impact adoption, abandonment and scale-up of AI approaches from the perspective of hospital staff, and from published guidelines and recommendations. The lack of robust technological infrastructure emerged as a barrier, where outdated networks, limited bandwidth, or poorly maintained servers could produce delays in AI outputs.^{15,22–25} Additionally, the need to run third-party software could introduce privacy barriers within hospitals.²² Challenges integrating the AI into tools already used by clinicians was also recognised.¹⁵ Whilst the ability for AI to integrate within existing computational resources and platforms that are secure enough for hospital IT structures were recognised as facilitators.²²

Concerns around the quality and relevance of data being fed into AI platforms^{15,17,22,23,26–30} and the excessive time it takes to enter and process the data^{22,23,31} were raised as barriers. The lack of interpretability and transparency of AI models was also recognised as an issue,^{15,25,29,30,32–35} whereas ensuring interpretable AI tools have user-friendly interfaces was a facilitator.^{22,29,30,36} Whilst the reduction of false alarms could help to prevent

abandonment, and scale-up the adoption of the tool.^{15,22,23,26} Concerns that AI outputs may have limited efficacy or accuracy, and may create an unnecessary burden to the user's workflow were challenges.^{22,26}

External validation to ensure AI solutions were generalisable across different departments or hospitals was recognised as a factor impacting the spread of AI adoption.^{22,23,29,30,32,36} Reviews also identified challenges where AI models are not trained on up to date data, leading to model drift, where assumptions learned from older data may no longer produce accurate results when new data is entered into the model.^{22,25} The literature therefore recommended monitoring for model drift by checking if data being input into the model still aligns with data it was trained on.^{22,25,26} Additional barriers included AI systems that might perpetuate biases present in the training data.^{15,23,28,33,36} This can happen if the training data only includes information on a specific population, who may have different characteristics to the broader population, that the AI model is then used with.^{15,36}

Domain 3: The value proposition. The third NASSS domain examined whether the AI innovation was perceived to fill a need or produce value, and how this could impact the adoption, abandonment, scale-up and spread of the innovation. The reviews shared that the lack of clarity on the relevance,²² lack of empirical evidence on the rigorous

evaluation or the added value of AI could be a barrier.^{15,16,26,29} Other reviews suggested conducting research studies to evaluate the roll-out of AI and to show the impact of AI versus traditional approaches to show measurable gains such as cost-savings, improved workload and improved clinical outcomes.^{22,23,26,34} Another challenge was evaluating AI models when evaluators don't have the level of knowledge of staff in informatic institutions, restricting who can evaluate such models.²² Some reviews flagged that tools would likely have better uptake if they seemed useful and easy to use.^{33,37}

Domain 4: The adopter system. The fourth NASSS domain addressed hospital staff and patients' ability and willingness to adopt the AI solution. The reviews consistently found that staff receptiveness to AI was influenced by factors such as awareness, training, perceived autonomy, and trust.

A lack of trust was frequently reported due to a misunderstanding of outputs or concerns around the accuracy of the AI outputs.^{15,16,22-26,28,29,33} Reviews found that a facilitator in building trust was the experience users had of previously witnessing an AI solution making correct predictions.^{23,26} Often discussed as a contributor to the scepticism towards AI was the lack of training and education among staff.^{15,16,23,24,26,27,33,38} The provision of training and guidance for the use and interpretation of AI outputs was recognised as an enabler to facilitate trust and AI implementation.^{22,23,26,38}

Some reviews identified a fear among clinicians that AI could undermine their professional expertise and lead to a loss of skills,^{15,24,29,33,37,38} which could lead to job displacement,¹⁵ this finding aligned with reviews that reported that balancing the use of AI with clinician autonomy could be an enabler to its adoption.^{26,33,37,38} Additional barriers included the lack of clarity on whether clinicians would be liable for acting on AI-based recommendations,^{15,24,35,38} concerns that data would not be kept private and secure,^{33,37} and a lack of trust from patients accepting an AI diagnosis as opposed to a clinician's diagnosis.^{15,38} One of the facilitators identified included ensuring patients were consented to the use of their data in AI systems.^{15,35}

Another barrier was that some teams rolling out AI approaches, had not engaged with end-users early enough to gain their buy-in.^{15,16} There were a range of enablers cited around stakeholder engagement such as co-designing the AI solutions with those who were going to implement it or be affected by its implementation such as patients, healthcare professionals, and data scientists.^{22,23,26,29,38} The literature also cited the importance of developing a multi-disciplinary team including data scientists and clinicians who would be involved in implementing, promoting and tracking usage of the AI tool together.^{22,23,25,26} Other enablers included raising awareness about the tool, appointing champions to advocate for its use,^{22,23,25,26} and employing a full-time role who could help integrate the use of the tool among staff.^{22,26}

Domain 5: The organisation. The reviews detailed how organisational culture and resource constraints can impede or lead to abandonment of new technologies, and that organisations already receptive to digital health initiatives could be a facilitator to AI's adoption.²² Also highlighted as a barrier to adoption and scalability was the organisational cost of AI implementation, such as costs for: the AI solution; for the integration of AI into existing infrastructure; for training staff; for reserving staff time or appointing new job roles to implement the AI solution.^{15,22,23,25-27} Another point identified as a barrier to the sustainability of AI implementation, was the costs of maintaining the AI tool and maintaining the training among staff to use it.^{23,26,27}

Gaining buy-in from senior leadership emerged as an enabler in some reviews.^{22,23,26} Kamel Rahimi et al. highlighted that leadership backing allowed hospital teams to allocate staff time and resources to implement AI solutions.²² Smoothly and effectively integrating AI within existing workflows could be a challenge,^{15,22,24,25,27,29,37} and integration of AI that is non-disruptive and staggered could be a facilitator.^{22,23,26,34} Other enablers included having an implementation plan to provide guidance on the adoption of the AI solution, such as who would be responsible for receiving the alerts or notifications from the AI solution.^{22,24,25,32,33,35} Reviews also cited enablers to the scalability and spread, such as standardising how AI is rolled out across a hospital²² and ensuring staggered deployment of the AI across sites.²³

Domain 6: The wider context. NASSS's sixth domain addressed political, regulatory, economic, and sociocultural factors. A cross-cutting finding was that regulatory bodies and government actions can either bolster or undermine local AI initiatives. Many of the reviews discussed that the lack of national governance for the ethical and legal considerations of AI such as patient data protection, could be regarded as a barrier to adoption and spread of AI in hospitals.^{15,16,25,35,37} Another barrier was the lack of an agreed framework for regulators to use for the evaluation of AI models.^{15,29} The reviews highlighted that national initiatives were needed to facilitate AI adoption and spread into the hospital setting.^{22,25,30} Economic factors were also discussed across the reviews, where the high cost of AI could introduce barriers for health systems to adopt AI solutions. This could then lead to two-tiered health systems where some hospitals can access supportive AI solutions whilst others face barriers due to funding constraints.^{15,22}

Domain 7: Interactions between domains and adaptation over time. The final NASSS domain focused on factors that may shape the resilience and long-term viability of AI interventions. Some of the reviews captured factors that may impact the sustainability of the AI solutions over time. The reviews recognised the lack of approaches to continuously regulate AI algorithms that keep changing over time,¹⁵ or to

track the impact of AI initiatives and feedback from users could be a barrier to sustainable solutions.^{23,29} The reviews highlighted improvement cycles could facilitate the sustainability of the AI solution, based on live feedback of the AI as it's being implemented, with quality assurance teams identifying and fixing errors.^{22,23,26} One review also cited enablers such as preparing an AI model to anticipate future data shifts through proactive learning,²² and using an open-source pipeline to allow for the addition of future new algorithms.²² Finally, a barrier cited previously in the organisation and wider system domains was the substantial economic costs of ongoing maintenance and ongoing training, which could impact the implementation of the tool over time.^{25,26}

Discussion

This umbrella review has offered a broad perspective on the factors acting as barriers and facilitators influencing the adoption, abandonment, scalability, spread, and sustainability of AI approaches in hospital settings globally. Although the included systematic reviews covered diverse regions of the world, and diverse clinical contexts from operating room management, infection prevention, critical care, and wearable patient monitoring, certain cross cutting insights emerged.

A factor reported to influence the adoption of AI solutions was healthcare professionals' trust in and understanding of the AI solution.^{2,15,22,23,26,27,31,38} Implementation science has long shown that healthcare professionals' scepticism or poor understanding of a new intervention routinely obstructs roll out. This is consistent with existing literature on healthcare professionals' perspectives on e-health interventions, or complex interventions more generally whereby a lack of understanding, lack of training, or lack of trust for a specific intervention or solution can affect implementation.^{41,42} As this barrier was cited across the international literature, it is important to note that national health organisations globally are now showing that they recognise the importance in ensuring an understanding of AI systems, and have goals to build healthcare workers' confidence in AI through training. This has been demonstrated by examples of national initiatives in the recently published OECD report on Scaling Artificial Intelligence in Health.⁴³ The report highlights that 11 countries (Australia, Czechia, Denmark, Estonia, Finland, France, Korea, Latvia, New Zealand, Sweden and UK) are now aiming to roll-out a national approach to improve health workforce awareness and competency with AI.⁴³

The spread and scalability of AI solutions was cited to be enabled by solutions that have been externally validated to ensure generalisability across different contexts such as departments and hospitals.^{22,23,26} Generalisability of research findings across different hospitals is a goal across

most health research.⁴⁴ However, there is a growing debate that the generalisability of machine learning models across different hospitals is unachievable due to the substantial differences in the operational characteristics of hospitals. Instead, it may be more appropriate to replace external validation of an AI solution across hospitals with a local validation approach instead, by recognising the differences, and instead ensuring it works well within each setting it has been deployed.^{45–47}

To facilitate the sustainability of AI solutions, the cost of maintaining and regulating the AI solution needs to be considered.^{2,15,22,23,26,27} These are areas that specific countries are now focussing on, as cited in the OECD report.⁴³ Countries such as the UK and France have confirmed large defined sums of investment into AI in healthcare.⁴³ France has also been cited as rolling out national legislation to govern AI in healthcare, with other countries likely following suit.⁴³ The OECD report indicates that many of the barriers and facilitators identified in this umbrella review are recognised internationally, and the ongoing efforts cited in the report to address these factors are encouraging for AI's implementation in hospitals.

The strengths of this review include that it has been guided by the NASSS framework from the outset, ensuring that data extraction and synthesis systematically captured the domains related to AI implementation and sustainability in hospitals. This research leveraged a large, multidisciplinary research team, allowing us to conduct double quality appraisal on all included articles, and conduct double screening and double data extraction for a subsample of publications. However, a significant limitation in our research is that the research team could not conduct double screening with all the publications, only the 25% subsample of publications. Another limitation is that important terms may have been missed from our search criteria when running the searches on databases, as there were two eligible articles identified from the scoping Google Scholar search, that were not picked up from the database search. We used the ROBIS tool for critical appraisal and have highlighted where some of the reviews included face methodological shortcomings and should therefore be interpreted with caution. We also recognise that 13 reviews contained some of the same included literature, which we have tried to overcome by not quantifying the specific factors cited as barriers or facilitators.

Conclusion

This umbrella review pinpointed both the facilitators and barriers for adopting AI solutions in hospitals. Through the NASSS framework we have been able to emphasise how the technology, perceived value, the adopter system, the organisation, the wider context and sustainability of the AI solution over time may affect AI's implementation. The

common factors that affected adoption included a lack of trust in and understanding of the AI solutions, whilst scale-up and spread was affected by the generalisability of the AI models. Sustainability was affected by the availability of funds and resources to maintain the AI solution. Some of the factors that acted as facilitators in implementation included co-design activities, comprehensive training, and gaining buy in from senior leadership. The development of national policies, nationally backed funding, and transparent national regulation of AI in healthcare would also support the implementation of AI in hospital settings at scale.

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Data Availability Statement

Data collected for this review will be shared upon request.

Disclaimer

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Supplemental material

Supplemental material for this article is available online.

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