

ARTIFICIAL INTELLIGENCE (AI) FOR HOSPITAL QUALITY IMPROVEMENT AND PATIENT SAFETY : A BIBLIOMETRIC-SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Purpose/Background: Artificial intelligence (AI) is increasingly applied in hospital settings to support risk prediction, clinical decision support, medication safety, adverse event detection, and operational improvement. However, evidence regarding whether AI provides added value over manual processes, rule-based alerts, non-AI systems, or standard clinical judgement remains fragmented and insufficiently consolidated.

Design/Methodology/Approach: This bibliometric-systematic literature review analyzed 65 Scopus-indexed articles published between 2021 and 2026. VOSviewer was used to map keyword co-occurrence, while Biblioshiny supported descriptive and thematic analyses. The synthesis examined AI technologies, hospital service domains, quality and safety outcomes, implementation patterns, study limitations, and evidence gaps.

Findings: Publication output increased after 2023 and peaked in 2024, with health informatics journals and Chinese institutions contributing prominently. Seven major clusters were identified: predictive analytics, algorithmic risk modelling, clinical decision support and early warning, EHR/EMR- and NLP-based adverse event detection, medication safety, deep learning in critical and specialty care, and operational efficiency. The strongest evidence involved prospective risk stratification for sepsis, falls, postoperative complications, mortality, readmission, length of stay, adverse drug events, and medication errors. Nevertheless, the evidence remains stronger for model accuracy and discrimination than for direct reductions in preventable harm.

Research limitations/implications: This review was limited to English-language Scopus-indexed articles and may not capture evidence from other databases or non-journal sources. Future studies should prioritize multicentre validation, pragmatic implementation trials, workflow evaluation, fairness, explainability, privacy, and post-deployment monitoring.

Practical implications: Hospitals should evaluate AI based on workflow integration, clinical actionability, governance, and measurable quality and safety outcomes rather than accuracy metrics alone.

Originality/value: This review integrates bibliometric mapping and systematic synthesis to position AI as an infrastructure for prospective risk governance in hospitals, rather than a replacement for clinical judgement.

Keyword : artificial intelligence; hospital quality; patient safety; machine learning; bibliometric-systematic review

Pendahuluan

Peningkatan mutu rumah sakit dan keselamatan pasien kini sangat bergantung pada pengelolaan data klinis dan operasional yang cerdas. AI dimanfaatkan pada berbagai area berisiko tinggi, seperti IGD, ICU, bedah, layanan perioperatif, nefrologi, onkologi, rehabilitasi, keselamatan obat, dan manajemen operasional. Teknologi ini digunakan untuk memprediksi sepsis, risiko jatuh, komplikasi, readmisi, mortalitas, lama rawat, medication errors, dan deteriorasi klinis. AI bekerja melalui machine learning, deep learning, NLP, predictive analytics, dan sistem pendukung keputusan klinis. Namun, bukti dampaknya terhadap penurunan kejadian tidak diharapkan masih terbatas, sehingga perlu evaluasi

implementasi, generalisasi, penerimaan klinisi, serta perbandingan dengan proses manual dan sistem non-AI secara berkelanjutan terukur.

Methods (Metode)

Penelitian ini menggunakan desain bibliometric-systematic literature review. Pencarian dilakukan di Scopus pada 6 Juni 2026, dibatasi pada artikel jurnal berbahasa Inggris tahun 2021-2026. Scopus dipilih karena menyediakan metadata bibliografis, sitasi, kata kunci, abstrak, dan format ekspor yang kompatibel dengan VOSviewer dan Biblioshiny. Strategi pencarian memadukan istilah AI, setting rumah sakit, mutu, keselamatan pasien, serta pembandingan/implementasi

Tabel 1. Strategi Pencarian Scopus

(TITLE ("artificial intelligence" OR "machine learning" OR "deep learning" OR "clinical decision support" OR "predictive analytics") AND TITLE-ABS-KEY (hospital* OR "acute care hospital*" OR "tertiary hospital*" OR "inpatient care") AND TITLE-ABS-KEY ("patient safety" OR "quality of care" OR "quality improvement" OR "healthcare quality" OR "adverse event*" OR "medication error*") AND TITLE-ABS-KEY ("usual care" OR "standard care" OR conventional OR "manual process*" OR "rule based" OR "clinical judgment" OR "clinical judgement" OR compar*) AND AUTHKEY ("artificial intelligence" OR "machine learning" OR "deep learning" OR "clinical decision support" OR "predictive analytics" OR "patient safety" OR "quality of care" OR "quality improvement" OR "adverse event*" OR "medication error*")) AND PUBYEAR > 2020 AND PUBYEAR < 2027 AND NOT TITLE-ABS-KEY (veterinar* OR "animal hospital*" OR dental OR dentistry OR "dental clinic*" OR radiomics OR pathology OR genomics OR "drug discovery") AND LIMIT-TO (DOCTYPE , "ar") AND LIMIT-TO (LANGUAGE , "English")

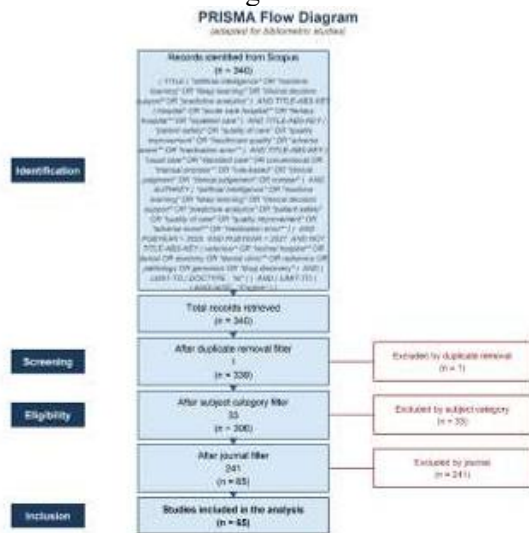
Tabel 2. Kriteria Inklusi dan Eksklusi

Inklusi Eksklusi	Inklusi Eksklusi
RS akut/tersier, IGD, ICU, rawat inap/jalan RS, farmasi klinik, unit mutu, komite keselamatan, atau sistem informasi klinis RS. Komunitas, layanan primer, aplikasi konsumen, wearable mandiri, atau telehealth tanpa relevansi langsung.	RS akut/tersier, IGD, ICU, rawat inap/jalan RS, farmasi klinik, unit mutu, komite keselamatan, atau sistem informasi klinis RS. Komunitas, layanan primer, aplikasi konsumen, wearable mandiri, atau telehealth tanpa relevansi langsung.
AI, ML, DL, NLP, predictive analytics, automated surveillance, atau CDSS berbasis AI. Sistem digital umum, dashboard, EHR/RME, atau rule-based alert tanpa komponen AI/ML/NLP.	AI, ML, DL, NLP, predictive analytics, automated surveillance, atau CDSS berbasis AI. Sistem digital umum, dashboard, EHR/RME, atau rule-based alert tanpa komponen AI/ML/NLP.
Keselamatan pasien, mutu, adverse events, medication errors, akurasi diagnostik, early warning, mortalitas, readmisi, audit, PREMs/PROMs, budaya keselamatan. Pengembangan algoritme teknis tanpa relevansi klinis, mutu, keselamatan, operasional, atau implementasi.	Keselamatan pasien, mutu, adverse events, medication errors, akurasi diagnostik, early warning, mortalitas, readmisi, audit, PREMs/PROMs, budaya keselamatan. Pengembangan algoritme teknis tanpa relevansi klinis, mutu, keselamatan, operasional, atau implementasi.
Pembandingan eksplisit/implisit dengan manual, usual care, pertimbangan klinis standar, rule-based, non-AI, atau pra implementasi. Tidak relevan dengan pembandingan, implementasi, atau perbaikan mutu/keselamatan.	Pembandingan eksplisit/implisit dengan manual, usual care, pertimbangan klinis standar, rule-based, non-AI, atau pra implementasi. Tidak relevan dengan pembandingan, implementasi, atau perbaikan mutu/keselamatan.
Riset orisinal, validasi, implementasi, tinjauan sistematis/scoping, atau bibliometrik peer-	Riset orisinal, validasi, implementasi, tinjauan sistematis/scoping, atau bibliometrik peer-

reviewed. Editorial, opini, surat, berita, blog, white paper vendor, atau tanpa metode jelas.	reviewed. Editorial, opini, surat, berita, blog, white paper vendor, atau tanpa metode jelas.
Judul, penulis, tahun, sumber, abstrak, kata kunci, dan identitas publikasi terverifikasi. Metadata tidak memadai atau identitas tidak dapat diverifikasi.	Judul, penulis, tahun, sumber, abstrak, kata kunci, dan identitas publikasi terverifikasi. Metadata tidak memadai atau identitas tidak dapat diverifikasi.
Artikel berbahasa Inggris, 2021-2026. Non-Inggris atau di luar periode.	Artikel berbahasa Inggris, 2021-2026. Non-Inggris atau di luar periode.

Skринing mengikuti PRISMA 2020 (Page et al., 2021). Dari 340 rekaman awal, satu duplikasi dihapus sehingga 339 rekaman disaring; 306 rekaman dipertahankan untuk penilaian kelayakan. Setelah telaah teks lengkap dan eksklusi karena fokus non-RS, AI tidak jelas, luaran tidak relevan, atau metode tidak memadai, 65 studi masuk sintesis akhir. Data diekstraksi mencakup penulis, tahun, desain, sampel, teknologi AI, domain layanan, luaran mutu/keselamatan, temuan, keterbatasan, kata kunci, dan sitasi.

Gambar 1. Diagram Alur PRISMA

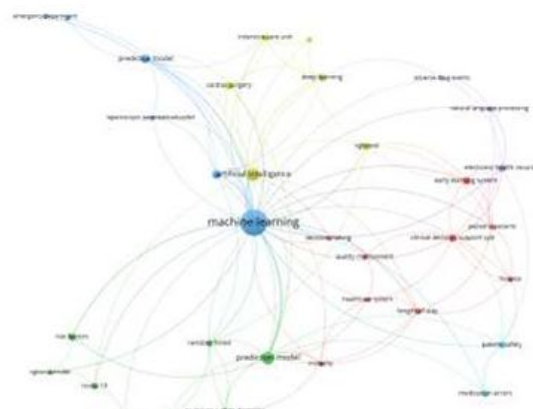


Analisis bibliometrik menggunakan VOSviewer dan Biblioshiny. VOSviewer memetakan ko-okurensi kata kunci dengan full counting dan ambang minimum 28, sedangkan Biblioshiny digunakan untuk analisis kinerja, tren publikasi, sumber, penulis, negara, sitasi, serta peta tematik

berdasarkan centrality dan density. Hasil bibliometrik diintegrasikan dengan sintesis bukti agar kluster mencerminkan substansi, bukan sekadar frekuensi istilah.

Results and Discussion (Hasil dan Pembahasan) Kluster Kata Kunci

Gambar 2. Peta Ko-okurensi



Peta ko-okurensi menunjukkan machine learning sebagai pusat metodologis yang menghubungkan prediction model, artificial intelligence, random forest, XGBoost, deep learning, CDSS, EHR/RME, early warning system, medication errors, dan patient safety. AI berperan mengubah data rumah sakit menjadi intelijen keselamatan prediktif, tetapi patient safety, medication errors, adverse drug events, NLP, dan sinyal keselamatan pasien masih kurang sentral dibandingkan model development (Hu et al., 2022; Zitu et al., 2023; Huang et al., 2022; Chen & Xu, 2023; Guo et al., 2024; Calvo-Cidoncha et al., 2022; Martenot et al., 2022; Trojan et al., 2024).

Tabel 3. Klaster Kata Kunci

Klaster	Artikel	Tema	Makna Utama
C1	13	Analitik prediktif berbasis ML	Prediksi risiko klinis, deteriorasi, komplikasi, mortalitas, sepsis, jatuh, perdarahan, dan luaran.
C2	8	Faktor risiko dan model algoritmik	Pengembangan model, validasi, interpretabilitas, dan generalisasi.
C3	6	CDSS dan peringatan dini	Pergeseran dari prediksi pasif ke alert, early warning, CDSS, dan peningkatan mutu.
C4	3	EHR/RME dan NLP	EHR/RME, NLP, dan text mining untuk adverse events serta sinyal tersembunyi
C5	8	Keselamatan obat/pasien	Medication errors, adverse drug events, prescribing safety, intervensi apoteker, pencegahan harm
C6	16	Deep learning kritis/spesialistik	ICU, bedah, kardiologi, nefrologi, neurologi, onkologi, dan layanan risiko tinggi
C7	11	Efisiensi operasional/LOS	Prediksi LOS, readmisi, demand, kelayakan rawat jalan, dan efisiensi sumber daya

Research Gap dan Agenda Lanjutan

Kesenjangan utama adalah bukti implementasi luaran klinis dunia nyata yang masih terbatas. Banyak studi melaporkan AUC, sensitivitas, spesifisitas, akurasi, atau validasi internal, tetapi belum membuktikan penurunan adverse events, medication errors, mortalitas, readmisi, failure to-rescue, atau LOS dibandingkan manual review, rule-based alert, usual care, atau pertimbangan

klinis standar (Shi et al., 2025; Chen et al., 2023a; Han et al., 2025; Welvaars et al., 2023; Mohammadi et al., 2024). Tantangan berikutnya mencakup integrasi workflow, akuntabilitas, validasi eksternal, generalisasi, patient-reported safety, keluhan, PREMs/PROMs, fairness, explainability, privacy, alert fatigue, dan monitoring pasca implementasi (Flückiger et al., 2024; Yi et al., 2025; Spiegel et al., 2024; Trojan et al., 2024).

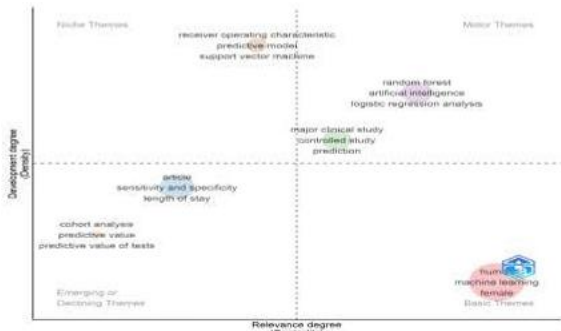
Tabel 4. Research Gap

Prioritas	Kesenjangan	Rasional	Implikasi	Pertanyaan
1	Bukti luaran klinis terbatas	Dominan metrik akurasi/validasi internal, bukan harm reduction.	AI berhasil teknis, belum tentu klinis.	Apakah AI menurunkan adverse events, errors, mortalitas, readmisi, atau LOS?
2	Workflow dan akuntabilitas terbatas	Penerimaan, trust, override, dan tindak lanjut belum jelas.	Risiko alert fatigue.	Bagaimana klinisi menindaklanjuti alert AI?
3	Validasi eksternal lemah	Banyak model dari satu RS/populasi/EHR.	Kinerja lokal belum tentu aman.	Apa penentu validitas eksternal?
4	Analitik pengalaman pasien terbatas	Prediksi klinis dan keselamatan obat dominan.	Sinyal pasien belum optimal.	Bagaimana NLP membaca keluhan/PREMs/PROMs?
5	Fairness/tata kelola terbatas	Bias, auditabilitas, transparansi, akuntabilitas belum konsisten.	AI dapat memperkuat ketimpangan.	Bagaimana tata kelola AI yang adil?

Bibliometrik Deskriptif dan Peta Tematik

Dataset mencakup 65 artikel Scopus, 39 sumber, dan 413 penulis, dengan rerata 12,14 sitasi per dokumen. Publikasi meningkat hingga puncak 2024 dengan 21 artikel; 2026 ditafsirkan hati-hati karena belum lengkap. Sumber paling produktif adalah BMC Medical Informatics and Decision Making (11 artikel; H-index lokal tertinggi), diikuti Annals of Medicine, BMC Surgery, Frontiers in Pharmacology dan Scientific Reports. Liu Y menjadi penulis paling produktif, diikuti Li L dan Li Y. Tiongkok mendominasi produksi dan sitasi (393 sitasi), diikuti Amerika Serikat, Inggris, Israel, dan Norwegia.

Gambar 5. Peta Tematik



Peta tematik menunjukkan random forest, artificial intelligence, logistic regression analysis, controlled study, dan prediction sebagai motor themes. Machine learning, human dan female menjadi basic themes; receiver operating characteristic, predictive model, dan support vector machine menjadi niche themes; sedangkan cohort

analysis, predictive value, sensitivity and specificity serta length of stay masih 5 | Page emerging/transitional. Pola ini menegaskan dominasi model prediktif dan perlunya penguatan implementasi klinis.

Sintesis Literatur

AI dipahami sebagai infrastruktur mutu dan keselamatan antisipatif melalui prediksi risiko dan early warning untuk berbagai luaran klinis (Shi et al., 2025; Chen et al., 2023a; Han et al., 2025; Zhang et al., 2024b; Jiang et al., 2024; Kim et al., 2025), sekaligus menggeser telaah insiden retrospektif menuju stratifikasi risiko prospektif (Ren et al., 2026; Wang et al., 2024; Zhang et al., 2025d; Yan et al., 2024), meski bukti masih lebih kuat pada model discrimination daripada harm reduction (Welvaars et al., 2023; Natarajan et al., 2026; Mohammadi et al., 2024). AI juga mendukung CDSS, keselamatan obat, alur operasional, pencegahan ekstubasi, CLABSI, rehabilitasi, prediksi demand IGD, perencanaan bedah, dan efisiensi kamar operasi (Flückiger et al., 2024; Abdo et al., 2024; Dai et al., 2022; Yi et al., 2025; Calvo-Cidoncha et al., 2022; Chen et al., 2026b; Spiegel et al., 2024; Saverino et al., 2021; Vollmer et al., 2021; Zhu et al., 2025), tetapi generalisasi, model kompleks, dan analitik pengalaman pasien masih menjadi tantangan utama dalam implementasi klinis berkelanjutan (Zitu et al., 2023; Millarch et al., 2023; Berge et al., 2023; Trojan et al., 2024).

Tabel 5. Tema dari Sintesis Literatur

Tema	Sintesis	Contoh Bukti
Prediksi risiko dan early warning	ML/DL memprediksi risiko sebelum adverse events: sepsis, hipotensi, jatuh, infeksi, AKI, gagal ekstubasi, mortalitas, readmisi, dan LOS.	Sepsis pediatrik/pascatransplantasi, risiko jatuh, ARDS pascabedah jantung, hipotensi pascainduksi, ventilator dependence, code blue/late intervention (Shi et al., 2025; Chen et al., 2023a; Zhang et al., 2024b; Chen et al., 2025; Jiang et al., 2024; Kim et al., 2025).
CDSS dan keselamatan obat	AI/CDSS mendukung prescribing safety, deprescribing, rekonsiliasi obat, antikoagulasi, prioritasasi pasien, dan	Deteksi PPI risk, prescribing-error alerts, prioritasasi medication errors berbasis ML, dan intervensi apoteker (Flückiger et al., 2024; Calvo-Cidoncha et al., 2022; Abdo et al., 2024; Yi et al., 2025).
Optimasi mutu dan operasional	AI mengoptimalkan workflow, LOS, kapasitas, surgery, clinical information retrieval, planning, monitoring, dan risk management.	Rehabilitasi pandemi, ED demand forecasting, surgical duration, phase recognition, hip revision planning, continuous model evaluation (Saverino et al., 2021; Vollmer et al., 2021; Langenberger et al., 2025; Golany et al., 2022; Zhu et al., 2025; Natarajan et al., 2026).

AI paling kuat sebagai prediksi risiko bila terhubung dengan workflow dan tindakan klinis, terutama CDSS, intervensi apoteker, ekstubasi tidak terencana, dan CLABSI (Chen et al., 2026b; Flückiger et al., 2024; Yi et al., 2025; Spiegel et al., 2024; Zhang et al., 2025c). Model tetap memerlukan interpretabilitas, validasi eksternal, evaluasi berkelanjutan, dan uji transfer lintas RS karena dipengaruhi prevalensi, workflow, volume kasus, serta ketidakseimbangan data (Ren et al., 2026; Lin et al., 2026; Zhang et al., 2024a; Natarajan et al., 2026; Mohammadi et al., 2024; Zitu et al., 2023; Millarch et al., 2023; Welvaars et al., 2023; Mohammadi et al., 2024). Model kompleks tidak selalu unggul, sementara bukti luaran langsung masih terbatas (Huang et al., 2022; Liu et al., 2024; Berge et al., 2023; Calvo Cidoncha et al., 2022; Yi et al., 2025; Chen et al., 2026b; Spiegel et al., 2024; Kim et al., 2025).

Pembahasan

Riset AI untuk mutu rumah sakit dan keselamatan pasien berkembang cepat, tetapi masih didominasi prediksi dan model development. AI mengubah data rutin menjadi intelijen keselamatan prediktif dan mendukung tata kelola risiko prospektif. Namun, patient safety, medication errors, adverse drug events, NLP, dan patient-reported outcomes belum sekuat model development. Temuan ini konsisten dengan studi prediksi sepsis, jatuh, komplikasi pascaoperasi, mortalitas, readmisi, LOS, transfusi, adverse drug events, dan deteriorasi klinis (Shi et al., 2025; Chen et al., 2023; Huang et al., 2022; Guo et al., 2024; Kim et al., 2025). Secara teoretis, AI memperluas keselamatan pasien dari incident reporting dan root cause analysis menuju pembelajaran prediktif-preventif, tetapi kecanggihan algoritmik harus diimbangi explainability, actionability, 7 | Page accountability dan clinical governance (Vollmer et al., 2021; Liu et al., 2024; Berge et al., 2023). Secara praktis, rumah sakit tidak cukup menilai AI dari AUC, sensitivitas, atau spesifisitas. AI harus dievaluasi berdasarkan integrasi workflow, intervensi dini, keselamatan obat, readmisi, LOS, tata kelola, dan monitoring pascaimplementasi. Validasi eksternal, bias assessment, explainability, data governance dan post-deployment surveillance penting karena performa model dapat menurun pada populasi, EHR/RME, dokumentasi, dan workflow berbeda (Zitu et al., 2023; Millarch et al., 2023; Mohammadi et al., 2024). Keterbatasan kajian ini mencakup penggunaan Scopus saja, pembatasan artikel Inggris, ketergantungan metadata, serta

dominasi studi retrospektif/model development. Penelitian berikutnya perlu menguji dampak AI terhadap adverse events, medication errors, mortalitas, readmisi, failure-to-rescue, LOS, trust, override, usability, PREMs, PROMs, diagnostic safety, fairness, auditability, privacy, accountability

Conclusion (Simpulan)

AI berkembang sebagai infrastruktur strategis untuk peningkatan mutu rumah sakit dan keselamatan pasien melalui prediksi risiko, CDSS, peringatan dini, deteksi adverse event, keselamatan obat, deep learning pada layanan kritis, dan perbaikan operasional. AI memberi nilai tambah dibanding proses manual, sistem non-AI, rule-based alerts, dan pertimbangan klinis standar karena mampu mengolah data besar dan multidimensional. Namun, bukti masih lebih kuat pada akurasi algoritmik daripada penurunan langsung adverse events, medication errors, mortalitas, readmisi, atau LOS. Kemajuan berikutnya bergantung pada sistem AI yang akuntabel, tervalidasi, adil, explainable, terintegrasi dalam workflow, dan berorientasi pada luaran keselamatan pasien.

Daftar Singkatan

Singkatan	Kepanjangan	Keterangan dalam Penelitian
AI	Artificial Intelligence	Kecerdasan buatan yang digunakan untuk prediksi risiko, dukungan keputusan klinis, keselamatan obat, deteksi kejadian merugikan, dan peningkatan mutu rumah sakit.
AKI	Acute Kidney Injury Acute Respiratory Distress Syndrome	Cedera ginjal akut; salah satu luaran klinis yang dapat diprediksi menggunakan model AI. Sindrom gangguan pernapasan akut; termasuk luaran klinis berisiko tinggi yang dianalisis dalam konteks pre
ARDS	Acute Kidney Injury Acute Respiratory Distress Syndrome	Cedera ginjal akut; salah satu luaran klinis yang dapat diprediksi menggunakan model AI. Sindrom gangguan pernapasan akut; termasuk luaran klinis berisiko tinggi

		yang dianalisis dalam konteks pre
AUC	Area Under the Curve	Ukuran kinerja diskriminatif model prediksi, terutama dalam menilai kemampuan model membedakan pasien berisiko dan tidak berisiko.
B-SLR	Bibliometric Systematic Literature Review	Pendekatan kajian yang menggabungkan analisis bibliometrik dan tinjauan literatur sistematis.
CDSS	Clinical Decision Support System	Sistem pendukung keputusan klinis yang membantu tenaga kesehatan dalam interpretasi data, peringatan dini, dan pengambilan keputusan.
CLABSI	Central Line Associated Bloodstream Infection	Infeksi aliran darah yang berhubungan dengan kateter vena sentral; digunakan sebagai salah satu indikator mutu dan keselamatan pasien.
DL	Deep Learning	Cabang machine learning yang menggunakan jaringan saraf berlapis untuk menganalisis data kompleks, terutama pada layanan kritis dan spesialisik
ED	Emergency Department	Unit gawat darurat; padanan internasional dari IGD dalam konteks literatur berbahasa Inggris.
EHR	Electronic Health Record	Rekam kesehatan elektronik yang menjadi salah satu sumber data utama untuk pengembangan model AI.
EMR	Electronic Medical Record	Rekam medis elektronik; sumber data klinis terstruktur maupun tidak

		terstruktur untuk analisis AI.
ICU	Intensive Care Unit	Unit perawatan intensif; area berisiko tinggi yang banyak menjadi lokasi penerapan AI untuk prediksi deteriorasi, mortalitas, dan komplikasi.
IGD	Instalasi Gawat Darurat	Unit pelayanan gawat darurat di rumah sakit yang menjadi salah satu domain penerapan AI untuk prediksi risiko dan demand pelayanan.
LOS	Length of Stay	Lama rawat pasien; salah satu indikator operasional dan luaran mutu yang dapat diprediksi menggunakan AI.
ML	Machine Learning	Pembelajaran mesin; pendekatan AI yang digunakan untuk membangun model prediksi risiko, klasifikasi, dan stratifikasi pasien.
NLP	Natural Language Processing	Pemrosesan bahasa alami untuk menganalisis teks klinis, narasi pasien, keluhan, dan data tidak terstruktur lainnya.
PPI	Proton Pump Inhibitor	Kelompok obat yang muncul dalam konteks keselamatan obat dan evaluasi penggunaan obat berbasis CDSS.
PREMs	Patient-Reported Experience Measures	Ukuran pengalaman pasien yang dilaporkan langsung oleh pasien dan dapat digunakan sebagai sumber data mutu pelayanan.
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta Analyses	Pedoman pelaporan yang digunakan untuk menggambarkan proses identifikasi, skrining, kelayakan, dan inklusi studi.

PROMs	Patient-Reported Outcome Measures	Ukuran luaran kesehatan yang dilaporkan langsung oleh pasien dan relevan untuk evaluasi mutu berpusat pada pasien.
RME	Rekam Medis Elektronik	Padanan Indonesia dari EMR/EHR; sumber data utama untuk pengembangan, validasi, dan implementasi AI di rumah sakit.
ROC	Receiver Operating Characteristic	Kurva untuk mengevaluasi kinerja klasifikasi model prediktif, biasanya berkaitan dengan nilai AUC.
RS	Rumah Sakit	Institusi pelayanan kesehatan yang menjadi konteks utama penelitian ini.
VOSviewer	Visualization of Similarities Viewer	Perangkat lunak bibliometrik yang digunakan untuk pemetaan ko okurensi kata kunci dan visualisasi jaringan literatur.
XGBoost	Extreme Gradient Boosting	Algoritme machine learning berbasis boosting yang sering digunakan untuk pemodelan prediktif dan stratifikasi risiko.

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