Journal of Pharmacy

Role of Artificial Intelligence and Real-Time Clinical Decision Support System in Enhancing Antimicrobial Stewardship for Pneumonia Management: A Scoping Review

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Abstract

Antimicrobial resistance (AMR) is a major public health challenge globally, particularly in pneumonia where inappropriate antibiotic use is common, resulting in increased morbidity and mortality. Artificial intelligence (AI) and clinical decision support systems (CDSS) have emerged as key tools to enhance antimicrobial stewardship (AMS) practices and reduce AMR. This scoping review aims to present and map the current AI and real-time CDSS applications in AMS for pneumonia patients, focusing on their types used and associated outcomes. This scoping review was conducted according to Arksey and O'Malley methodological framework and reported according to the PRISMA-ScR checklist. Databases including PubMed, CINAHL, EMBASE, and Scopus, were searched between April and August 2025. Original studies published in English between 2015 and 2025 were included. Out of 505 identified articles, 11 eligible studies were analysed. The findings showed that AI and CDSS tools, when integrated with machine learning (ML) algorithms and large databases, enhance diagnostic accuracy, optimise antibiotic use, improve pathogen identification, enhance AMR detection, promote guideline adherence, and support treatment-related decisions, thereby reducing mortality, healthcare costs, and the overuse of broad-spectrum antibiotics. However, integrating these technologies into clinical workflows remains a challenge due to limited research in low- and middle-income countries, data quality issues, and associated ethical concerns. AI and the CDSS are promising technologies to enhance AMS, especially in pneumonia, with improved patient outcomes. Future research to validate these technologies in diverse settings, while addressing barriers to their implementation and ethical concerns, is needed to enhance AMS practices and reduce AMR globally.

Article history:

Received: 14 Nov 2025
Accepted: 22 January 2026
Published: 31 January 2024

Keywords:

Pneumonia
Antimicrobial Stewardship
Artificial Intelligence
Clinical Decision Support System
Antibiotic Resistance

doi: 10.31436/jop.v6i1.463

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Introduction

Respiratory infections remain one of the leading health challenges worldwide, causing significant morbidity and mortality across all age groups (Niederman & Torres, 2022). Among these, pneumonia stands out as a major contributor to the global disease burden particularly affecting patients admitted to intensive care units (ICUs) (Torres et al., 2017). According to the 2021 Global Burden of Disease (GBD) report, 2.1 million people die from pneumonia, including over 500,000 children under the age of 5 and approximately 1 million adults over the age of 70 (Bender et al., 2024).

Pneumonia is caused primarily by *Streptococcus pneumoniae* but can also have bacterial or viral origins, leading to inflammation of the lungs (Gadsby Naomi & Musher Daniel, 2022). Antibiotic therapy is primarily used to treat pneumonia, with selection on the basis of co-morbidities, patient health conditions, pathogen types, and patterns of antibiotic resistance (Cilloniz et al., 2016). In recent years, the push for improved antimicrobial stewardship (AMS) has led to the acceptance of shorter, 5-day treatment courses, especially for less severe infections. Nonetheless, certain types of pneumonia pathogens, such as *Legionella pneumoniae*, may still require longer antibiotic treatments (10-14 days) on the basis of clinical experience rather than clinical trial evidence (Lim, 2022).

Clinically, distinguishing between these aetiologies at presentation is challenging. As a result, antibiotics are often prescribed empirically for pneumonia cases, even when the infection may be viral, leading to frequent unnecessary antibiotic use (Szymczak et al., 2024). This over-prescription not only exposes patients to potential side effects but also leads to the emergence of antimicrobial resistance (AMR). AMR has become a critical worldwide concern, and the mismanagement of pneumonia plays a significant role in this crisis. Over 1.5 million deaths were associated with drug-resistant lower respiratory infections in 2019 (Murray et al., 2022). This makes pneumonia and related illnesses the most burdensome infectious syndrome in terms of the impact of AMR. Recognising this threat, the World Health Organisation (WHO) has urged healthcare systems to strengthen AMS as a core strategy to combat AMR (WHO, 2023). AMS refers to coordinated strategies aimed at optimising antibiotic use (CDC, 2024). AMS plays a significant role in preventing the overuse of antibiotics and, consequently, the emergence of AMR (ACSQHC, 2023). In pneumonia management, the irrational use of broad-spectrum antibiotics in suspected pneumonia accelerates the AMR while disrupting the normal microbiota (Pennisi et al., 2025). Thus, improving antibiotic decision-making in pneumonia is crucial for both improving patient outcomes and slowing the spread of resistant pathogens. However, achieving consistent and timely optimisation of antibiotic use in routine clinical practice remains challenging.

Traditional AMS interventions, such as clinician education, post-prescription audit-and-feedback, and antibiotic restriction policies, have had success in improving prescribing behaviours (WHO, 2019). However, their impact could be inconsistent and labour-intensive (Gorman et al., 2016). AMS can be particularly challenging in the ICUs. One recent study in an ICU found that a focused AMS significantly reduced broad-spectrum antibiotic days for pneumonia patients without compromising safety (Sekandarzad et al., 2025). The question remains: how can such optimisation be implemented more efficiently and in real time across diverse clinical contexts?

This challenge has prompted growing interest in digital approaches to support AMS. Innovations in digital health such as Artificial intelligence (AI), with machine learning (ML) as its core methodological subset, and Clinical Decision Support Systems (CDSS) have emerged as transformative tools for enhancing AMS in pneumonia care (Pennisi et al., 2025). CDSS offer a promising strategy to promote targeted and guideline-based antibiotic use. When integrated with AI, the CDSS assists healthcare providers in selecting the most appropriate therapy based on patient data and established guidelines through programmed algorithms or AI models (Duvel et al., 2025). A narrative review of CDSS from 2019-2023 identified 28 studies of antimicrobial prescribing CDSS, the majority embedded in electronic health record (EHR) systems. Notably, most of these tools targeted antibiotic decisions and were implemented in hospital settings (Bienvenu et al., 2025). Overall, such systems have shown promising potential, with majority of studies reported that CDSS use led to reductions in inappropriate antibiotic use or improved compliance with prescribing guidelines. Nevertheless, traditional CDSS often use fixed algorithms and may not capture the full complexity of clinical scenarios, a gap that AI is well-positioned to fill (Bienvenu et al., 2025).

AI enables real-time, data-driven decision-making by integrating complex clinical datasets, microbiological results, and genomic information to strengthen AMS programs worldwide (Pinto-de-Sa et al., 2024). AI-driven CDSS play crucial roles in reducing antibiotic misuse, supporting targeted antibiotic therapy, and mitigating AMR (Bilal et al., 2025; Pennisi et al., 2025). Studies have demonstrated that CDSS reduce inappropriate antibiotic prescribing and improve clinical outcomes (Laka et al., 2020; Rittmann & Stevens, 2019).

Despite these promising developments, evidence specific to pneumonia-focused AMS remains fragmented. This scoping review aims to systematically map and descriptively synthesise the existing evidence on the application of AI and CDSS in enhancing AMS for pneumonia management, including the types of AI and CDSS interventions used, their associated outcomes, and their role in improving antibiotic prescribing decisions, diagnostic accuracy, guideline adherence, and the predictive identification of patients at higher risk of AMR.

Materials and methods

Study Design and Databases

This scoping review was conducted following the Arksey and O'Malley (2005) methodological framework for scoping reviews (Arksey & O'malley, 2005), and was further refined by the Levac et al. (2010) framework (Levac et al., 2010). The findings are reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist to ensure transparency (Tricco et al., 2018). A scoping review methodology was selected due to the heterogeneity and emerging nature of AI and CDSS based interventions in AMS for pneumonia management. Unlike systematic reviews, which focus on evaluating narrowly defined interventions, a scoping review is more suitable for mapping the broad range of existing evidence, study designs, and outcomes, as well as identifying knowledge gaps and clarifying key concepts (Munn et al., 2018). Databases, including PubMed, CINAHL, EBSCO, Embase, and Scopus, were searched between April and August 2025 to find relevant research articles.

Search Strategy

Boolean logic was used as a search strategy to retrieve articles. All terms related to the scope of the research were divided into concepts and searched individually and in combination. The detailed Boolean logic search strategy is presented in Table 1.

Research Questions

The research questions were built using the Population, Concept, and Context (PCC) framework provided by the Joanna Briggs Institute (JBI) (Pollock et al., 2023). According to this framework the population (P) in this study includes patients with pneumonia. The concept (C) is the role of AI and CDSS tools in enhancing AMS. The context (C) is the settings where pneumonia cases are managed and AMS practices are followed, such as in any healthcare setting. Based on this PCC framework, the primary research question was:

- What evidence exists on the use of artificial intelligence (AI) and clinical decision support systems (CDSS) to enhance antimicrobial stewardship in the management of pneumonia among patients across healthcare settings?

Table 1: Boolean logic search strategy to retrieve data

Concept	Search Terms
AI-related terms	"Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Predictive Analysis" OR "Deep Learning"
Clinical Decision Support System	AND "Clinical Decision Support System" OR "CDSS"
Antimicrobial Stewardship terms	AND "Antimicrobial Stewardship" OR "Antibiotic Stewardship" OR "AMS" OR "ASP"
Pneumonia-related terms	AND "Pneumonia" OR "Community Acquired Pneumonia" OR "CAP" OR "Ventilator Associated Pneumonia" OR "VAP" OR "Hospital Acquired Pneumonia" OR "HAP"

Secondary research questions were:

- What types of AI and CDSS interventions have been reported to support antimicrobial stewardship in pneumonia management?
- What functional roles of AI and CDSS (e.g. diagnosis support, treatment optimisation, antibiotic selection, and AMR detection) have been reported in antimicrobial stewardship for pneumonia?
- What antimicrobial stewardship–related and patient outcomes have been reported in studies evaluating AI and CDSS use in pneumonia management?
- What barriers and challenges to implementing AI- and CDSS-based interventions for antimicrobial stewardship in pneumonia management have been reported?

Inclusion and Exclusion Criteria

The inclusion criteria comprised original research articles evaluating the role of AI, ML, or CDSS in antimicrobial stewardship for pneumonia management, limited to English-language publications from the past 10 years (2015–2025). Studies exploring the role of predictive analytics and AI models in identifying patients at risk of antibiotic resistance were also included. Studies published before 2015, as well as systematic reviews, meta-analyses, narrative reviews, scoping reviews, literature reviews, and non-peer-reviewed studies, were excluded from the review.

Study Selection

The titles and abstracts of the studies were initially reviewed by one investigator independently (MJH), followed by approval from a second reviewer (NSAR). The full-text articles were then assessed by three independent investigators (NEA, ZAH, and SR). Any disagreements regarding the study selection process were discussed and resolved. Studies that met the inclusion criteria were included in the review. All the articles were downloaded and reviewed manually for this study.

Data Extraction and Charting

Data were extracted from the selected studies via a standardized data collection procedure for scoping reviews (UniSA, 2025). Key details about the studies, such as the title, author details, year of publication, study location, aims/objectives, methodology, study design, study population, intervention (AI tool or CDSS), outcomes, research findings, limitations, and conclusions, were recorded in a research matrix chart to visualize and organise the information.

Results

A total of 505 records were identified through database and supplementary searches. After the removal of 133 duplicate records, a total of 372 records were screened. Following title and abstract screening, 258 articles were excluded: studies not related to AMS/AI/CDSS/pneumonia (n=172) and non-original research (n=86). A total of 114 full-text articles were assessed for eligibility, of which 103 were excluded based on the inclusion and exclusion criteria: review articles (n=25), non-pneumonia studies (n=22; studies in which pneumonia was mentioned only incidentally or as a subgroup and was not the primary study population or main clinical focus), studies outside the date range (n=18), and studies without an AMS/AI/CDSS focus (n=38). Finally, 11 studies that met the criteria were included in the scoping review and analysed. The PRISMA flow diagram outlining the study selection process is shown in Fig. 1.

Study Design and Intervention Types

Most of the studies employed a retrospective design (n=6) (Chakshu & Nithiarasu, 2022; Free et al., 2023; Jian et al., 2024a, 2024b; Lin et al., 2024; Müller et al., 2021), with a smaller number using quasi-experimental trials (n=2) (Ciarkowski et al., 2020; Dean et al., 2015), interrupted time series (n=1) (Khadem et al., 2022), cluster-controlled trial (n=1) (Dean et al., 2022), and randomised controlled trials (RCTs) (n=1) (Gohil et al., 2024). Most interventions were implemented in hospital-based workflows, commonly in emergency department or ICU settings, with some delivered through tele-AMS models (Chakshu & Nithiarasu, 2022; Dean et al., 2015; Dean et al., 2022; Jian et al., 2024a; Khadem et al., 2022). An overview of all included studies is presented in Table 2. Overall, the evidence base is dominated by retrospective and quasi-experimental designs, with comparatively limited randomised evaluation of clinical impact

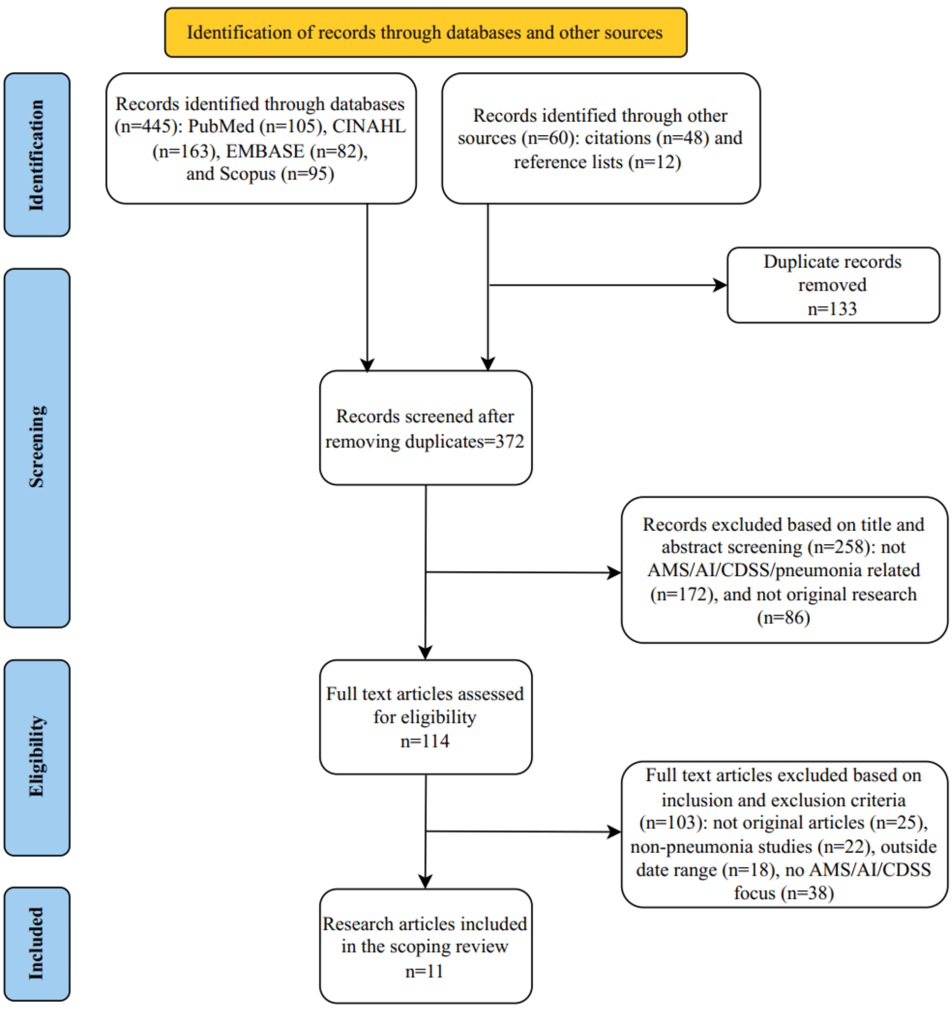

Fig. 1: PRISMA flowchart of included studies

Table 2: Overview of selected research articles for scoping review

Sr. No.	Authors	Year	Country	Study type	Summarized Aim/Objective
1	Lin et al.	2024	Taiwan	Retrospective study	Develop AI-CDSS for rapid antibiotic resistance detection
2	Jian et al.	2024a	Taiwan	Retrospective study	Develop AI-CDSS for rapid detection of carbapenems-resistant *Klebsiella pneumoniae*
3	Jian et al.	2024b	Taiwan	Retrospective study	Develop AI-CDSS for predicting quinolone resistance
4	Gohil et al.	2024	USA	Randomised clinical trial	Evaluate CPOE (computerized provider order entry) prompts on antibiotic selection
5	Free et al.	2023	UK	Retrospective study	Develop framework for clinical decision support in CAP
6	Khadem et al.	2022	USA	Interrupted Time Series	Assess impact of CDSS on antimicrobial usage
7	Chakshu & Nithiarasu	2022	UK	Retrospective study	AI-based digital twin for pneumonia treatment
8	Dean et al.	2022	USA	Cluster-controlled trial	Evaluate electronic pneumonia clinical decision support (ePNa) in pneumonia treatment
9	Müller et al.	2021	USA	Retrospective study	Develop iBiogram for patient-specific antimicrobial therapy
10	Ciarkowski et al.	2020	USA	Quasi-experimental study	Evaluate CDS tool for CAP treatment supplemented by AMS review
11	Dean et al.	2015	USA	Quasi-experimental study	Evaluate effect of real-time electronic CDSS on pneumonia management

Additionally, most studies have focused on improving diagnostic accuracy and AMR detection, with AI playing a key role in enhancing clinical decision-making and supporting AMS efforts (Chakshu & Nithiarasu, 2022; Dean et al., 2015; Gohil et al., 2024; Jian et al., 2024a, 2024b; Lin et al., 2024; Müller et al., 2021). A detailed summary of the selected studies characteristics is provided in Table 3.

Geographical Distribution

The 11 studies included in this review were conducted across various countries, with the majority originating from the United States (USA) Fig.2. This geographical distribution highlights a concentrated interest in AI and the CDSS for pneumonia management in high-income settings, primarily the USA and Taiwan, with fewer studies from the United Kingdom (UK).

Scope of Aims

The aims of the studies were categorised on the basis of shared characteristics. Across the included studies, aims clustered into four domains: (1) rapid pathogen identification and AMR detection, (2) risk stratification and severity prediction, (3) prescribing optimisation e.g., antibiotic selection or reduction

Table 3: Summary of study characteristics included in the scoping review

Sr. No	Authors	Study Population (Sample Size)	Outcomes	Research Findings	Advantages	Limitations
1	Lin et al. (2024)	107,721 bacterial samples	Improved clinical decision process and Improved antibiotic resistance detection in *Klebsiella pneumoniae*	High accuracy and precision for predicting CZA resistance (highest AUC=0.95 in LGBM, GBC, and RF models; highest accuracy=0.90 in the LGBM model; highest sensitivity=0.88 in the GBC model; highest specificity=0.91 in the LGBM model; and highest F1=0.88 in the LGBM model)	Enhanced speed of resistance detection	Lack of generalisability of data in diverse clinical settings data quality affects performance
2	Jian et al. (2024a)	52,827 bacterial samples	Accurate and fast identification of resistant pathogens and precise antibiotic use	Improved, quick and precise antibiotic resistance detection (CRKP: highest AUC=0.96 in the RF model, highest accuracy=0.89 in the RF and LGBM model, highest sensitivity=0.90 in GB and LGBM model, highest specificity=0.90 in RF model, and highest F1 score=0.88 in RF, GB, and LGBM model) and (CoRKP: highest AUC=0.98 in the RF model, highest accuracy=0.93 in the XGBoost model, highest sensitivity=0.95 in the XGBoost model, highest specificity=0.91 in the RF model, and highest F1=0.93 in RF and XGBoost models)	Cost-effective, precise and fast identification of resistant pathogens	Limited to 5 hospitals, lacks diversity and generalisability of data
3	Jian et al. (2024b)	165,299 bacterial samples	Improved detection of quinolone-resistant strains	High predictive accuracy for CIP resistance (highest AUC=0.95 in the RF, LGBM, GBC, and XGBoost models, highest accuracy=0.90 in the LGBM model, highest sensitivity=0.92 in the GBC model, highest specificity=0.91 in the LGBM model, and highest F1=0.88 in the LGBM model and LEV resistance (highest AUC=0.95 in the RF and GBC models, highest accuracy=0.87 in the GBC model, highest sensitivity=0.89 in the RF model, highest specificity=0.86 in the GBC model, and highest F1=0.88 in the GBC model	High precision in detecting resistant, faster and accurate diagnosis and improved antibiotic selection and use	Limited by the data quality and model generalisability
4	Gohil et al. (2024)	44,780 pneumonia patients	Reduced use of empiric antibiotic	Significant reduction in extended-spectrum antibiotic use (approximately 28.4%; 95% CI=0.66-0.78 and *p-value* < 0.001)	Supports optimal AMS and significant reduction in antibiotic use	Applicability limited to private-community hospitals

5	Free et al. (2023)	630 CAP patients	Enhanced pneumonia management	Improved prioritisation of pneumonia cases (244 (70.3%) unreviewed patients with moderate or high-severity pneumonia were found using the automated EASUL system)	Improved prioritisation and effective decision-making	Limited by missing data and the complexity of integrating data from multiple sources
6	Khadem et al. (2022)	100 patients	Reduced antimicrobial usage	Significant reduction in antimicrobial use (approximately 11%, level change, *p-value* < 0.0001)	Faster and accurate antibiotic selection	Inconsistent intervention documentation and short time frames
7	Chakshu & Nithiarasu (2022)	1895 patients	Improved treatment selection and treatment prioritisation	High precision in identifying important outcomes for patients with pneumonia (probability of death: AUROC=0.89, 95% CI=0.88-0.91, accuracy=0.88, probability of needing mechanical ventilation: AUROC=0.84, 95% CI=0.82-0.86, accuracy=0.72)	High prediction accuracy and real-time prioritisation of pneumonia cases	Limited to pneumonia cases in ICU
8	Dean et al. (2022)	6,848 ED pneumonia patients	Reduced 30-day mortality rate and antibiotic use in pneumonia patients	Decreased 30-day mortality (adjusted OR=0.62, 95% CI=0.49-0.79, *p-value* < 0.001) and increased guideline-concordant antibiotic prescribing (83.5% to 90.2%, *p-value* < 0.001)	Increased adherence to guidelines, improved patient care and outcomes	Limited to specific hospitals settings only and randomisation not possible
9	Müller et al. (2021)	30,761 patients	Better antimicrobial therapy and reduced mortality in high-risk conditions	Better risk-based antibiotic prescribing and enhanced AMS, with a proven decrease in the incidence of empiric therapy failure for high-mortality cases (from 11.6%-17.4% with real prescriptions to 7.8%--3% with iBiogram recommendations)	Data driven personalized prescribing	Retrospective nature limits external validity
10	Ciarkowski et al. (2020)	623 patients	Reduced IV antibiotic duration and cost	Improved healthcare value with a 20% cost reduction and shorter antibiotic medication duration	Cost-effective approach with similar clinical outcomes	Limited to a single academic medical centre
11	Dean et al. (2015)	4,758 ED pneumonia patients	Improved patient care and adherence to guidelines	Significantly reduced ED mortality for CAP patients (OR=0.53, 95% CI=0.28-0.99)	Standardisation of care and improved patient outcomes	Not randomised and no proper selection of large number of pneumonia patients

CZA: ceftazidime-avibactam, LGBM: light gradient boosting machine, RF: random forest, GBC: gradient boosting classifier, XGBoost: eXtreme gradient boosting, AUC: area under the curve, CRKP: carbapenems-resistant Klebsiella pneumoniae, CoRKP: colistin-resistant Klebsiella pneumonia, CIP: ciprofloxacin, LEV: levofloxacin, EASUL: embeddable AI and state-based understandable logic, AUROC: area under the receiver operating characteristic curve, CI: confidence interval, OR: odds

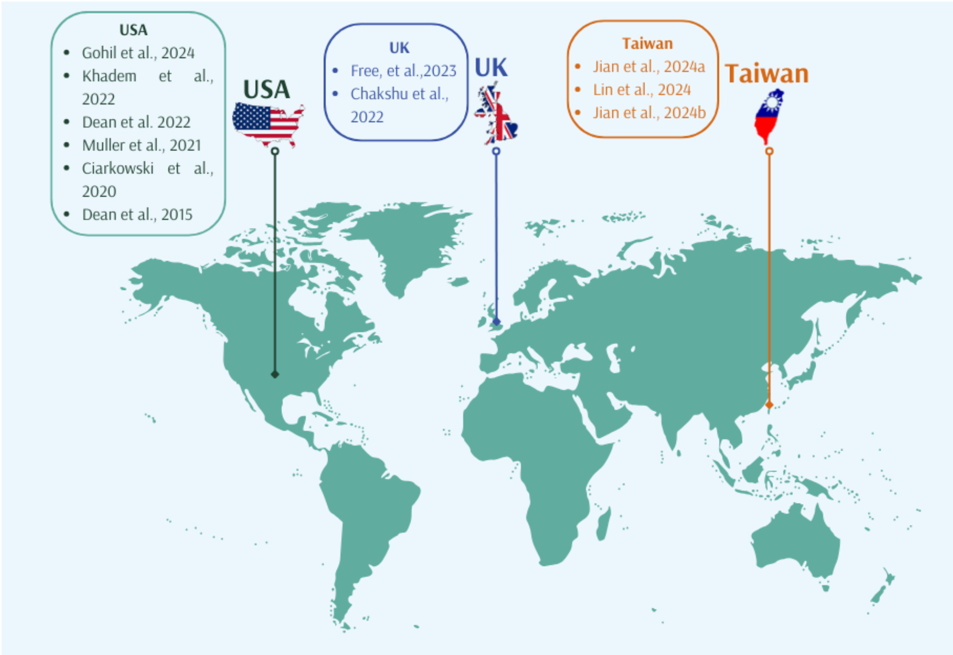

Fig. 2: Geographical distribution of studies

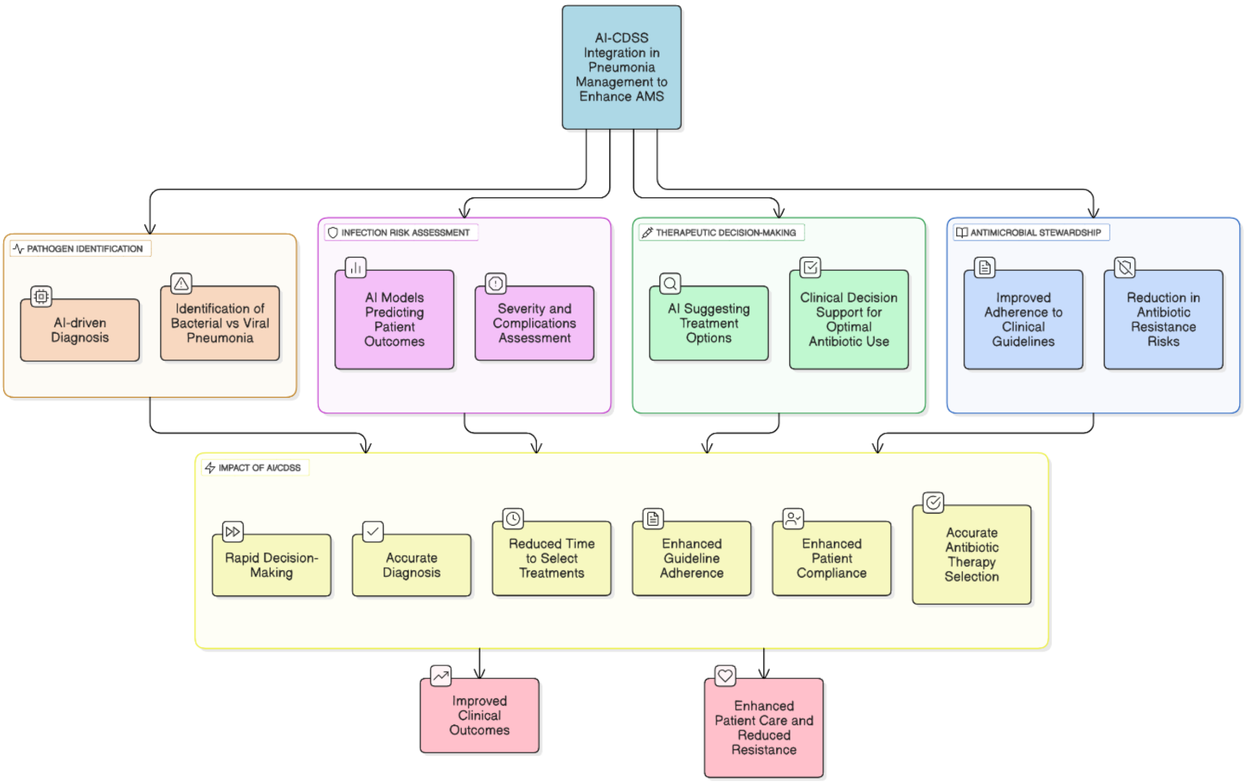

Fig. 3: Scope of aims of included studies

of broad-spectrum use), and (4) guideline adherence and pathway-based management. Fig. 3 illustrates the scope of aims across the included studies.

AI or CDSS Systems Used in Different Studies

A prominent trend is the integration of AI models with microbiological platforms, particularly MALDI-TOF MS, to enable rapid pathogen identification and AMR prediction. Other systems focused on prescribing optimisation through rule-based or probabilistic CDSS embedded within EHRs, while a smaller number employed advanced modelling approaches, such as digital twins and neural networks, for severity prediction and risk stratification. Overall, the diversity of systems reflects differing institutional priorities, with most tools targeting either early diagnostic support or real-time prescribing decisions rather than comprehensive end-to-end pneumonia management. The AI tools and CDSS systems used in the included studies are given in Table 4.

Although all these tools proved to be effective in managing pneumonia and enhancing AMS practices, every AI/CDSS system has its own significance and importance. For example, the different ML models used in the studies by Lin et al. (2024), Jian et al. (2024a), and Jian et al. (2024b) showed that when combined with MALDI-TOF MS, they improved diagnostic accuracy, particularly for detecting resistant pathogens in pneumonia patients. Across studies, outcome reporting was heterogeneous, with stronger evidence for diagnostic and AMR detection performance than for patient-centred clinical outcomes. Table 5 outlines the impact of AI/CDSS tools across the included studies, highlighting which outcomes were most improved to enhance AMS in pneumonia management.

Discussion

The digital transformation of healthcare is rapidly changing how infectious diseases, such as pneumonia, are managed. Technologies such as AI and real-time CDSS are becoming essential tools for improving AMS and patient outcomes (AlGain et al., 2025; Duvel et al., 2025). This scoping review aimed to map the current use of AI and real-time CDSS in managing pneumonia to enhance AMS. From an initial search of multiple databases for original research studies, 11 studies were included, demonstrating the growing integration of AI and the CDSS into AMS practices for pneumonia management. Most studies originated from the USA, Taiwan, and the UK, reflecting advanced healthcare systems available in these regions (Chakshu & Nithiarasu, 2022; Ciarkowski et al., 2020; Dean et al., 2015; Dean et al., 2022; Free et al., 2023; Gohil et al., 2024; Jian et al., 2024a, 2024b; Khadem et al., 2022; Lin et al., 2024; Müller et al., 2021), thereby highlighting a substantial evidence gap in low- and middle-income countries (LMICs), where the AMR burden remains high yet insufficiently addressed (Otaigbe, 2023).

Table 4: AI and CDSS systems used in the included studies

Sr. No.	Authors	AI/CDSS System
1	Lin et al. (2024)	Matrix-assisted laser desorption/ionisation time-of-flight mass spectrometry (MALDI-TOF MS) + AI models (LGBM, GBC, Random forest classifier (RFC), and XGBoost).
2	Jian et al. (2024a)	MALDI-TOF MS + AI models (LGBM, RFC, GBC, RFC, XGBoost, and Support Vector Machine (SVM)).
3	Jian et al. (2024b)	MALDI-TOF MS + AI models (LGBM, RFC , GBC, AdaBoost classifier (ABC), and XGBoost).
4	Gohil et al. (2024)	CPOE prompts integrated with multidrug resistant organisms (MDRO) risk-based decision support.
5	Free et al. (2023)	Clinical decision system (CDS) called Embeddable AI and State-based Understandable Logic (EASUL).
6	Khadem et al. (2022)	ILUM Insight CDSS.
7	Chakshu & Nithiarasu (2022)	AI-based digital twin model with MLP (Multilayer Perceptron) and RNN (Recurrent Neural Networks) for severity prediction.
8	Dean et al. (2022)	Electronic pneumonia clinical decision support (ePNa).
9	Müller et al. (2021)	iBiogram CDSS with a probabilistic algorithm based on local antibiogram data.
10	Ciarkowski et al. (2020)	CDS-driven CAP pathway coupled with active AMS and provider feedback.
11	Dean et al. (2015)	Real-time electronic CDSS for pneumonia.

Our findings highlight that AI-CDSS tools primarily enhance diagnostic accuracy, pathogen identification, risk assessment, and adherence to clinical guidelines; optimise antibiotic selection; and reduce empirical broad-spectrum antibiotic use, thereby mitigating the spread of AMR (Chakshu & Nithiarasu, 2022; Dean et al., 2022; Gohil et al., 2024; Jian et al., 2024a, 2024b; Khadem et al., 2022; Lin et al., 2024). These findings are consistent with the study conducted by Rittmann & Stevens (2019), which highlighted that CDSS interventions improve antibiotic prescribing, reduce the use of broad-spectrum antibiotics, and increase adherence to AMS guidelines. However, the study also emphasised that although the effect of these interventions on certain outcomes is significant, it is not universal (Rittmann & Stevens, 2019). Therefore, whenever a new AI model or CDSS intervention system is developed, it is important to consider the structure of the healthcare setting and the context in which it will be implemented. Similarly, CDSS-driven prompts and frameworks were found to improve guideline adherence and decrease unnecessary antibiotic exposure in both community and hospital settings (Ciarkowski et al., 2020; Gohil et al., 2024), which is consistent with other findings showing that digital tools such as AI and CDSS enhance adherence to AMS protocols and improve the accuracy of antibiotic prescribing (Laka et al., 2020; Rittmann & Stevens, 2019).

ML models integrated with MALDI-TOF MS demonstrated rapid and precise detection of resistant *Klebsiella pneumoniae* strains, substantially shortening the time to appropriate therapy (Jian et al., 2024a, 2024b; Lin et al., 2024). Nguyen et al. (2024) also reported that combining AI with MALDI-TOF MS enables faster and more effective detection of AMR compared with conventional methods.

The predominance of retrospective studies (Chakshu & Nithiarasu, 2022; Free et al., 2023; Jian et al., 2024a, 2024b; Lin et al., 2024; Müller et al., 2021) and quasi-experimental designs (Ciarkowski et al., 2020; Dean et al., 2015) reflects both the emerging nature of AI and CDSS research and the challenges in conducting RCTs for digital interventions in clinical settings. However, most studies reported positive impacts, including reduced antibiotic use, better prioritisation of patients, and decreased mortality rates in pneumonia patients (Ciarkowski et al., 2020; Dean et al., 2022; Gohil et al., 2024).

Most AI approaches employed ML algorithms such as LGBM, RFC, SVM, and other advanced AI methods, capitalising on their strengths in pattern recognition and predictive modelling (Jian et al., 2024a, 2024b; Lin et al., 2024). Some studies have explored hybrid models that combine ML with deep learning to improve predictive performance, particularly in ICU and emergency contexts where pneumonia severity stratification is critical (Ciarkowski et al., 2020; Jian et al., 2024a, 2024b; Lin et al., 2024). These advanced methodologies facilitate real-time, patient-specific therapeutic recommendations, reducing the reliance on empiric broad-spectrum antibiotics that drive resistance development (Bilal et al., 2025; Pennisi et al., 2025; Pinto-de-Sa et al., 2024).

Despite these advances, several challenges remain. Many AI-CDSS tools have been developed and tested on data from specific hospitals or limited geographic regions, limiting their generalisability to other settings and patient populations and restricting their applicability to diverse clinical environments (Free et al., 2023; Jian et al., 2024b; Lin et al., 2024). Although the AI models and CDSS interventions in our review demonstrate high accuracy in development datasets, their clinical reliability is limited, especially when applied in other settings. These challenges have also been highlighted in various other studies (Behar et al., 2023; Rockenschaub et al., 2024). AI models trained on specific datasets show high performance, but when the same models are tested on different datasets, a substantial drop in performance is observed. For example, Rockenschaub et al. (2024) found that when the same model was applied to data from other hospitals, there was a decline in AUC of about 0.200, which limits the generalisability of the model. However, they suggested that training the model on multicentre datasets and continuously refining it could help mitigate this challenge. Furthermore, data quality and heterogeneity remain critical barriers that need to be addressed. The integration of AI and CDSS into existing EHR workflows is also a significant concern, as these systems often disrupt routine clinical practice and are not readily accepted by many clinicians (Dean et al., 2022; Free et al., 2023; Khadem et al., 2022).

Clinician acceptability and ethical concerns about AI-CDSS decision-making should also be addressed (Morley et al., 2020). There is a critical gap in evaluating the safety and implementation of these digital tools because none of the primary research included in this review address the ethical issues that arise when integrating them in standard healthcare settings. Theories like Technology Acceptance Model (TAM) are helpful to understand the adoption of technologies like AI and CDSS in routine clinical practice. This theory emphasises the importance of these technologies key determinants such as usefulness and ease of use (Panagoulias et al., 2023). Marinescu et al. (2025) found that getting the benefits from these technologies indicates that there are more chances of adoption of these technologies. Transparency in AI algorithms, accountability for recommendations, and robust data privacy safeguards are essential to enhance trust and responsible implementation. Ensuring that AI assists but, not replaces clinician judgment is critical for patient safety and efficacy (Morley et al., 2020).

Another significant concern is the lack of research on AI-CDSS applications across LMIC, where the AMR burden is often highest (Otaigbe, 2023). Consistent with the Diffusion of Innovation Theory, technology adoption occurs earlier in high-income countries, while LMICs face financial and infrastructural constraints, including limited EHR capacity (Alami et al., 2020; Zhang et al., 2015), highlighting the need for international collaboration, capacity building, and targeted infrastructure investment to enable equitable AI-CDSS implementation.

Study Significance

The increase in AMR is alarming, especially for the management of pneumonia, which is usually treated with empirical and broad-spectrum antibiotics, leading to inappropriate and excessive use of antibiotics. This scoping review significantly maps the available literature regarding the role of AI and the CDSS in enhancing AMS in pneumonia management. The findings highlight their role in improving diagnostic accuracy, patient compliance, and correct antibiotic selection; reducing AMR; and enhancing adherence to AMS guidelines, which led to reduced hospital stay and mortality rates. These findings provide valuable insights and might help physicians and policymakers explore more about the role of AI and the CDSS in transforming AMS practices and reducing AMR globally.

Research Gap

Despite these valuable findings, this scoping review also highlights significant gaps in the current literature regarding the role of AI and the CDSS in enhancing AMS. Very few studies have been conducted globally, and those that have been conducted are mainly from high-income countries where healthcare systems are well established. No studies have been conducted in LMIC, where the burden of AMR is significantly greater. Most studies were conducted in single centres or small clinical settings, which limits generalisability. Additionally, only a few studies have discussed the barriers to integrating AI and the CDSS into existing EHR systems and clinical workflows. Furthermore, none of the studies highlight or explore ethical concerns related to AI algorithms and data transparency. Therefore, future research should address these gaps through more robust, multicentre studies, especially in resource-constrained countries, to explore fully the global potential of these technologies in enhancing AMS and combating AMR worldwide.

Limitations

Limitations of the review include restrictions to English-language publications, which may have excluded relevant studies, particularly from regions where the pneumonia burden is high but research is less represented in English journals, and a lack of risk-of-bias assessment given the heterogeneity of the included study designs. Additionally, the inclusion of only original research articles, which might have excluded valuable information from review articles and other sources, potentially affects the comprehensiveness of the findings. Furthermore, the fast-evolving nature of AI research means that newer studies beyond the search window may offer further insights.

Conclusion

AI and the real-time CDSS are promising tools to enhance AMS in pneumonia management and to combat AMR. In clinical practice, these technologies can improve diagnostic accuracy, optimise antibiotic selection, promote guideline-concordant prescribing, and reduce inappropriate broad-spectrum antibiotic use, thereby strengthening stewardship practices and improving patient outcomes in routine clinical care. Future research should focus on validating these tools across diverse healthcare settings and exploring strategies for their effective, ethical, and scalable implementation.

Acknowledgement

The authors gratefully acknowledge all researchers whose work has been cited in this manuscript.

Conflict of Interest

The authors have no relevant conflicts of interest to disclose regarding this research.

Funding

The authors declare that no financial support, grants, or external funding were received for the preparation of this manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, AI-assisted technologies, including ChatGPT 5.0 (OpenAI) and DeepSeek-V3.2, were utilized to enhance readability and language. However, all generated content was thoroughly validated, reviewed, and edited by the author to ensure accuracy and coherence. The author takes full responsibility for the final content of this manuscript.

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