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A Comprehensive Review Of Methodologies In Clinical Data-Driven Decision Support Systems For Healthcare

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Abstract

Objectives:

This review aims to analyze recent advancements in clinical data-driven decision support systems (CDSS) in healthcare on 15 years period (2010-2024), focusing on the evolution from rule-based to machine learning and AI-driven models in broad sense. The goal is to examine key methodologies, trends, domain-specific applications, and the challenges faced in deploying these systems in real-world clinical environments.

Methods:

A systematic review of IEEE Xplore, Web of Science, PubMed and Scopus was conducted covering publications from 2010 to 2024. Inclusion criteria targeted articles discussing data-driven CDSS methodologies, including supervised learning, deep learning, hybrid systems, and explainable AI (XAI). A total of 954 papers were initially identified, 213 met eligibility criteria, and 50 were selected for detailed analysis.

Results:

We selected 50 papers, 34 of which describe approaches in the data-driven AI area, 11 present purely classical rule-based CDSS, and 5 adopt hybrid approaches relying on both rule-based and data-driven AI.

Conclusions:

Recent studies in clinical data-driven Decision Support Systems (CDSSs) show a shift toward data-driven AI methods. These can work alone in purely data-driven systems or be combined with classical rule-based CDSS in hybrid systems. Hybrid approaches integrate machine learning with domain knowledge, creating a synergy that improves reliability and effectiveness.This combination also helps address key challenges in healthcare, especially transparency, interpretability, and explainability, which are now central to both AI and medical informatics research.

Keywords: *Clinical Decision Support Systems (CDSS), Data-Driven Healthcare, Artificial Intelligence, Machine Learning Models.*

1 INTRODUCTION

Clinical data-driven decision support systems (CDSS) have become essential tools in modern healthcare, harnessing artificial intelligence (AI), machine learning (ML), and big data to assist clinical decision-making, improve patient outcomes, and reduce errors [1]. Over the past decade, CDSS capabilities have expanded substantially by leveraging advanced algorithms and large-scale datasets to support clinicians at the point of care [2][3]. Seminal works in decision support theory laid the foundation for data-driven approaches over a decade ago [6][7], marking a shift from static, rule-based expert systems to adaptive models that learn from clinical data. Early CDSS were predominantly rule-based, encoding medical knowledge as if-then rules, but as electronic health records (EHRs) and other large clinical databases became widely available, the field transitioned toward data-driven models capable of integrating multimodal data and generating real-time, personalized recommendations [8][9]. Comprehensive surveys have charted this evolution, highlighting how combining expert knowledge with data-driven insights can improve decision effectiveness in healthcare [8][9]. CDSS today can aggregate structured data (e.g. EHR entries, laboratory results) and unstructured data (e.g. free-text clinical notes, medical images, genomics), enabling more context-aware and patient-specific support for diagnosis and therapy planning [8][2][15]. This progression from knowledge-driven to data-driven systems has vastly increased the scope and impact of CDSS in clinical practice, as evidenced by improved adherence to guidelines and more informed clinical decisions reported across numerous studies [1][3][16].

Methodologically, the landscape of CDSS has diversified greatly over the last 15 years. Contemporary data-driven CDSS employ a wide range of AI techniques, from classical ML algorithms such as decision trees, random forests, and support vector machines to advanced deep learning models for complex data like medical imaging and

temporal signals [10][11][12]. Ensemble learning and other hybrid approaches (e.g. combining rule-based logic with statistical ML) have been explored to improve predictive performance and handle uncertainty in clinical data [8][20]. In addition, natural language processing is used to extract insights from clinical text, and techniques like fuzzy logic and Bayesian reasoning have been applied in domains where interpretability of rules is important. Modern CDSS architectures increasingly integrate multimodal and distributed data: for example, distributed learning frameworks and knowledge graphs enable collaborative reasoning over fragmented multi-center datasets while preserving privacy [12][13]. The convergence of cloud computing and business intelligence tools with CDSS further facilitates the analysis of large datasets and real-time decision support at scale [21]. Emerging technologies such as the Internet of Things (IoT) are also being incorporated; IoT-based CDSS can collect real-time patient data via wearables and remote monitors to support decisions in acute settings like emergency care [28]. Moreover, the integration of big data analytics is allowing CDSS to uncover patterns from population-scale health data that were previously infeasible to analyze, thereby improving predictive modeling for outcomes and resource utilization [19]. These methodological advances have broadened the application domains of CDSS. Indeed, AI-driven decision support tools have been developed across numerous medical specialties (e.g. oncology, cardiology, critical care, primary care), illustrating the generality of these techniques [18]. For instance, recent systems employ multimodal data integration and ML for cancer prognosis and treatment planning [12], personalized risk-based antimicrobial therapy in critical care [14], and chronic disease management through EHR-linked analytics [15]. Such domain-specific implementations demonstrate how CDSS are being tailored to diverse healthcare contexts while sharing common data-driven foundations.

Multiple evaluations and real-world studies have demonstrated the benefits of CDSS in clinical workflows, particularly in improving process measures and adherence to best practices. A number of high-quality systematic reviews and meta-analyses have found that CDSS usage is associated with significant improvements in healthcare process metrics such as compliance with clinical guidelines, monitoring protocols, and prescribing safety [3][16][17]. For example, a meta-analysis by Kwan *et al.* reported a 5.8% absolute increase in desired care processes when CDSS were implemented in clinical settings [3]. These systems have also been shown to enhance practitioners' performance in following evidence-based practices and reduce certain medication errors or oversight [16][17]. However, translating process-level improvements into tangible patient outcome benefits has proven more challenging. The impact of CDSS on clinical outcomes (e.g. mortality, morbidity, or overall patient health) is often modest or inconsistent, with several studies reporting only limited improvements in patient outcomes despite clear process gains [10][17]. Recent scoping reviews of ML-based CDSS found mixed effects on patient outcomes, noting that many systems function as assistive tools rather than independently driving major outcome changes [10]. In some cases, improvements in surrogate outcomes or intermediate endpoints are observed, but high heterogeneity across studies and contexts makes it difficult to generalize the clinical effectiveness of CDSS [17][3]. These findings highlight that while data-driven CDSS can unquestionably streamline processes and support clinical decision-making, rigorous evidence of long-term patient outcome improvement remains variable. Further research with robust study designs is needed to evaluate the conditions under which CDSS use translates into better clinical outcomes and cost-effectiveness.

Despite the considerable advancements, significant challenges and barriers continue to hinder the optimal implementation of CDSS in healthcare. Data quality and interoperability issues are persistent concerns – CDSS rely on integrating data from multiple sources, and inconsistent data standards or incomplete records can undermine system performance [21]. Ensuring that the knowledge bases and input data are accurate and up-to-date is labor-intensive, and poor data quality can lead to spurious recommendations or reduced clinician confidence in the system. Moreover, many CDSS still face difficulties with **workflow integration**: to be effective, these tools must seamlessly embed into clinicians' routine without causing alert fatigue or workflow disruptions. Studies of implementation factors underscore the importance of aligning CDSS with existing clinical processes, providing adequate user training, and tailoring recommendations to fit the context of care [29]. **Clinician trust and acceptability** of CDSS recommendations remain critical and somewhat elusive goals. Healthcare professionals often hesitate to fully rely on an AI-generated suggestion unless the system is transparent and explainable in its reasoning. Qualitative evaluations have found that while clinicians generally value the potential of data-driven decision support, they tend to fall back on their own judgment when a CDSS output is not easily interpretable or conflicts with their experience [22]. Indeed, trust and transparency are recurrent themes in CDSS research: a scoping review noted that improving the explainability of recommendations and providing evidence to support system outputs are vital for clinician acceptance [24]. Lack of explainability can impede adoption, as

users need to understand *why* a recommendation is made in order to feel comfortable acting on it [22][24]. This has led to a growing emphasis on **eXplainable AI (XAI)** techniques within CDSS to open the "black box" of ML models and present recommendations with interpretable justification [23]. In the context of active decision support (e.g. medication prescribing alerts), designing the human–computer interaction in a way that complements clinical reasoning rather than interrupting it is another ongoing challenge [25]. **Ethical and regulatory considerations** are also at the forefront as CDSS become more prevalent. Issues of data privacy, patient consent, algorithmic bias, and accountability for AI-driven decisions are increasingly prominent in the literature [20][23]. Ensuring compliance with health data protection regulations and addressing bias in training data are necessary to maintain public trust in these systems. There is a recognized need for robust frameworks and guidelines to govern the safe and responsible deployment of AI in clinical settings. Researchers have called for stronger validation of CDSS in diverse patient populations and more transparent reporting of algorithm performance to identify biases or gaps [26][27]. In sum, overcoming these socio-technical barriers – from improving data interoperability and model transparency to earning clinician trust and establishing ethical guardrails – is crucial for the next generation of CDSS.

In summary, the past decade has witnessed substantial progress in CDSS methodologies, moving from expert-driven systems to powerful data-driven and intelligent platforms. Major advancements in AI algorithms, data integration, and user interface design have expanded the capabilities and reach of clinical decision support. At the same time, the field has grappled with methodological evolution and real-world challenges, including variable impact on outcomes, integration into clinical workflows, and issues of trust, explainability, and governance. Recent comprehensive reviews echo that AI can greatly enhance CDSS functionality but also emphasize that many challenges remain before the full potential of these systems is realized [20]. Ongoing research is increasingly focused on addressing these challenges – for example, developing more generalizable and **robust CDSS validation** strategies, incorporating clinician-centered design principles, and instituting **responsible AI** practices to ensure fairness and accountability [23]. This review provides a synthesis of methodologies, implementations, and outcomes in data-driven CDSS from 2010 to 2025, drawing on high-impact studies in the field. The insights gathered here aim to highlight how far CDSS have come, evaluate what has and hasn't worked, and point to future directions for research and implementation – including interdisciplinary collaboration, improved transparency, and rigorous clinical evaluation – to ultimately achieve safe, effective, and trustworthy decision support in healthcare.

2 METHODS

A comprehensive search was conducted across IEEE Xplore, Web of Science, PubMed, and Scopus, covering literature from 2010 to 2024. The search strategy included terms related to clinical decision support systems, data-driven methodologies, machine learning, AI, implementation, and evaluation. In total, 954 papers were identified, 356 were screened after de-duplication, 213 met eligibility criteria, and the top 50 most relevant papers were included in this review.

2.1 Search Strategy

A systematic review was conducted across four major bibliographic repositories: IEEE Xplore, Web of Science (WoS), PubMed, and Scopus covering publications from January 2010 to December 2024.

- PubMed: Searches combined the MeSH terms "Clinical Data-driven Decision Support System" and "Artificial Intelligence" with the AND operator. To capture contributions not indexed with MeSH terms, additional keyword-based searches were performed in article titles, including "machine learning", "expert system", "information retrieval", and "cognitive aid". Since the query "machine learning" alone yielded overly broad results, a refined search required both "machine learning" AND "decision" in titles.
- Web of Science (WoS): As WoS does not support MeSH term filtering, the terms "Clinical Data-driven Decision Support System" and "Artificial Intelligence" were used in AND combination, restricting subject categories to Medical Informatics, Computer Science Artificial Intelligence, Computer Science Information Systems, and Computer Science Interdisciplinary Applications.
- IEEE Xplore: The database was queried with the terms "Clinical Data-driven Decision Support System" and "artificial intelligence" in AND combination. Additional refinements included keywords related to machine learning and healthcare decision support.
- Scopus: The database was searched using the terms "Clinical Data-driven Decision Support System" and "Artificial Intelligence" with the AND operator. To capture broader coverage, additional keyword searches

("machine learning", "expert system", "information retrieval", "cognitive aid") were applied to titles, abstracts, and keywords. Searches were further refined by limiting subject areas to Health Sciences, Computer Science, and Decision Sciences

Only English-language publications with accessible abstracts were considered.

2.2 Eligibility Criteria

Studies were included if they met at least one of the following criteria:

1. Described or implemented a clinical data-driven Decision Support System (CDSS).
2. Presented a review or comparative analysis of existing CDSS tools.
3. Addressed related issues such as interoperability, transparency, explainability, or preliminary CDSS design.

Studies were excluded if they did not describe a CDSS, were outside the clinical domain, or lacked methodological/clinical relevance.

2.3 Screening Process

The review was conducted in two stages:

1. Title and abstract screening: Both authors independently assessed the relevance of retrieved publications.
2. Full-text review: Articles not excluded in the first stage were read in full, with the workload equally divided between the two co-authors.

Any disagreements during the screening process were resolved through discussion and consensus.

2.4 PRISMA Flow Diagram

The review process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

- Records identified: All search queries across PubMed, WoS, Scopus, and IEEE Xplore yielded an initial set of N_1 articles.
- After duplicate removal: N_2 unique records remained.
- Title and abstract screening: N_3 records were excluded as not relevant.
- Full-text assessment: N_4 articles were reviewed in detail, with exclusions made for reasons such as non-clinical focus, insufficient methodological details, or lack of CDSS content.
- Final inclusion: N_5 studies were included in the systematic review and categorized according to methodology and clinical tasks.

A PRISMA flow diagram (Figure 1) visually summarizes the number of records identified, screened, excluded, and finally included in the review.

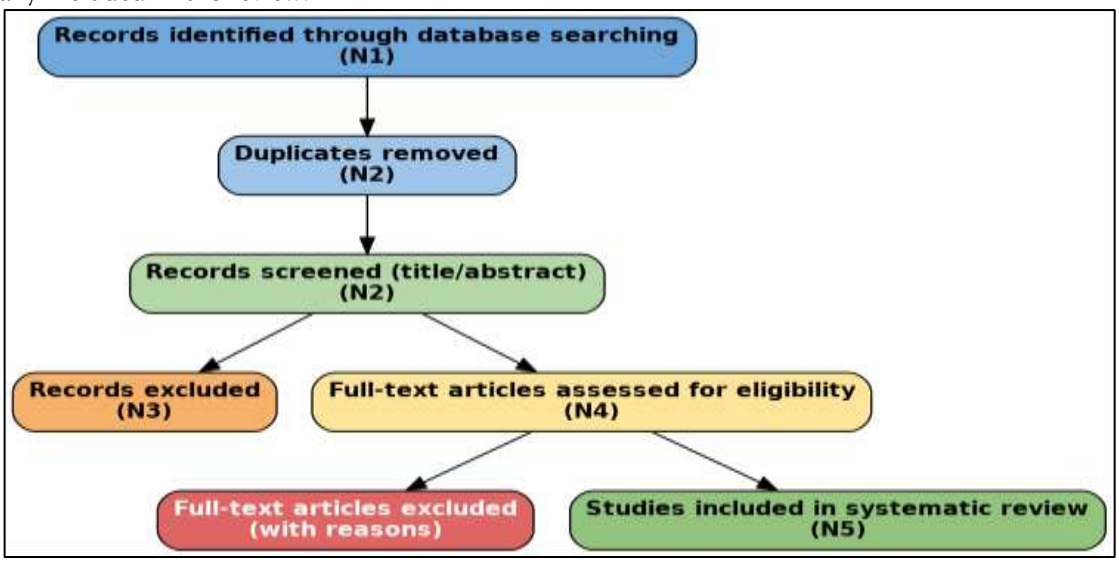

Figure 1 PRISMA flow diagram

2.5 Data Categorization

The final set of included studies was classified based on:

- Methodology: e.g., Data-driven AI, knowledge-based CDSS, and hybrid approaches.

- Clinical tasks supported: e.g., diagnosis, prognosis, treatment recommendation, risk stratification, or monitoring.

This categorization enabled the identification of trends in clinical data-driven CDSS research over the period 2010–2024.

3 RESULTS

A comprehensive search was conducted across PubMed, Web of Science (WoS), IEEE Xplore, and Scopus, covering the period from 2010 to 2024. The search strategy combined MeSH terms and keywords related to clinical data-driven decision support systems (CDSS), artificial intelligence, machine learning, expert systems, information retrieval, and cognitive aids. In total, 954 records were identified. After removal of duplicates, 356 papers remained for screening, of which 213 met the eligibility criteria. Finally, the 50 most relevant works were included for in-depth analysis.

The PubMed search retrieved records through both MeSH terms and keyword strategies. MeSH terms for "Clinical Data-driven Decision Support System" and "Artificial Intelligence" yielded 68 initial papers, with exclusions based on scope and duplication. Additional keyword searches produced further results ("machine learning AND decision": 15 papers; "expert system": 36 papers; "information retrieval": 31 papers; "cognitive aid": 6 papers). After full-text screening and de-duplication, 21 eligible papers were retained from PubMed. The WoS search identified 113 papers, restricted to the subject categories Medical Informatics, Computer Science (AI, Information Systems, Interdisciplinary Applications). Following abstract and full-text screening, 15 relevant works were retained, with duplicates cross-checked against PubMed results. The IEEE Xplore search combined "Clinical Data-driven Decision Support System" and "Artificial Intelligence," refined with healthcare and machine learning–related terms. The query identified 412 papers. After de-duplication and screening for relevance to CDSS methodology, implementation, or evaluation, 137 papers were included. The Scopus search retrieved 365 papers using a combination of title, abstract, and keyword terms ("Clinical Data-driven Decision Support System" AND "Artificial Intelligence"), complemented by additional keywords ("machine learning," "expert system," "information retrieval," "cognitive aid"). After exclusion of duplicates and off-topic studies, 40 papers met inclusion criteria.

In total, 50 studies were retained for final analysis. The overall review process is summarized in Figure 2. The included works were systematically classified according to their methodological orientation, distinguishing between data-driven and knowledge(rule)-based clinical decision support systems (CDSSs), with further refinement into relevant methodological subgroups. Studies adopting hybrid approaches were also identified. Furthermore, particular attention was given to the clinical tasks supported by each system. The detailed findings are reported in the subsequent subsections.

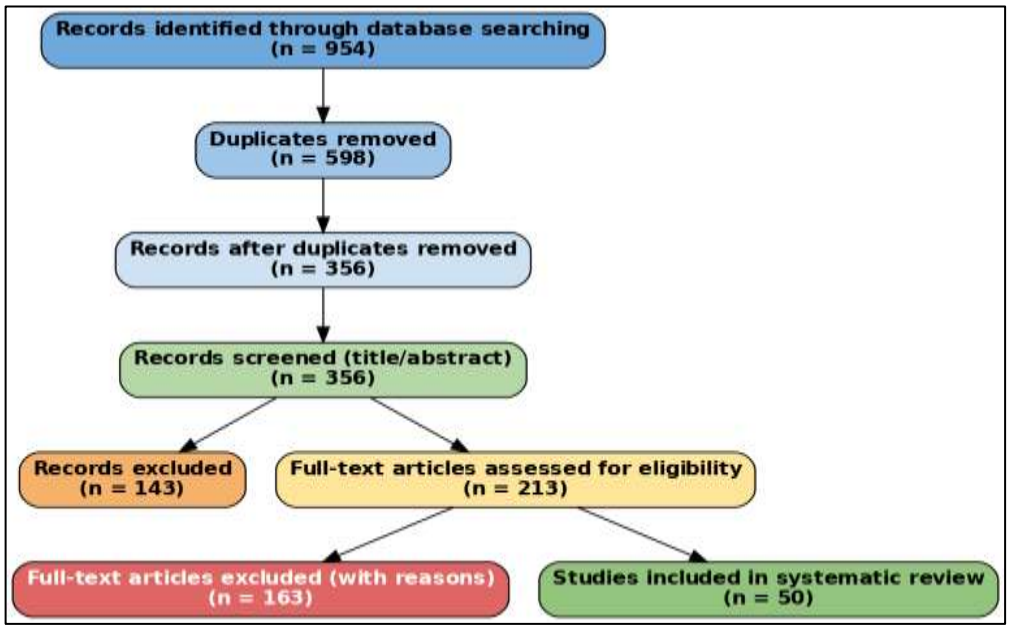

Figure 2 Flow of the review process.

3.1 Clinical Data-driven Decision Support (CDSSs):

Across the included literature, most studies used data-driven artificial intelligence (AI) to deliver clinical decision support (CDS) for prediction, triage, diagnosis, and risk stratification. Typical inputs were electronic health records (EHRs), imaging, bedside waveforms, and clinical text; methods ranged from regularized regression and tree-based ensembles to deep learning and multimodal fusion. Broad reviews chart the rapid growth of machine-learning (ML) CDS and its migration into real-world health systems, with emerging interest in multimodal and federated learning to cope with data silos and heterogeneity [31, 48, 55, 57,59, 60].

Representative tasks include early-warning and outcome prediction in emergency and acute care (e.g., sepsis mortality) [48, 53, 69]; automated imaging workflows that prioritize critical findings [31]; and ICU-focused models that learn temporal patterns from high-frequency data [53, 59, 60]. Natural-language processing (NLP) over EHR notes repeatedly appears as a key enabler for turning unstructured documentation into structured features for downstream CDS [63]. Comparative surveys indicate that deep neural architectures increasingly outperform traditional ML on high-dimensional signals, while tree-based ensembles remain competitive—and often easier to explain—for tabular EHR data [53, 59, 60]. Reinforcement learning has promise for sequential therapy optimization, though safety and off-policy evaluation remain barriers to deployment [61]. Multimodal learning improves discrimination and calibration where heterogeneous data are available [59, 60]. Privacy-preserving federated training is frequently proposed to overcome institutional data silos while respecting governance constraints [57].

Despite strong internal metrics (AUC/accuracy) in development settings, translation to patient outcomes is mixed. Meta-analyses across computerized CDS—spanning both earlier and modern systems—show modest absolute improvements in processes of care and heterogeneous, often small effects on hard clinical endpoints [30, 35, 38]. These patterns emphasize that implementation determinants—timely, context-aware delivery; workflow fit; and actionable recommendations—often dominate algorithmic accuracy in determining real-world benefit [32, 45, 51, 58]. Trust, transparency, and robustness are recurring adoption hurdles for black-box models, with risks such as dataset shift and biased labels [65], and ethics/regulatory imperatives around bias assessment and oversight [66, 72]. To support safer early use, DECIDE-AI provides reporting guidance for first-in-human evaluations of AI-driven CDS, emphasizing usability, failure modes, and human-factors testing [40, 41]. Explainable AI for tabular/time-series data aims to reconcile performance with clinician interpretability [76], complemented by XAI in imaging [68].

Finally, the learning-health-system paradigm—continuous data analysis feeding care improvement—appears across the corpus and aligns naturally with data-driven CDS [73]. Reviews of real-world and synthetic data underline opportunities to broaden external validation while protecting privacy and accelerating method development [70, 71]. Five systems in this group were hybrid (knowledge-augmented) and are cross-referenced in substion 3.3: Moja et al. [38], Roshanov et al. [45], Caballero-Ruíz et al. [44], Solares et al. [53], and Kline et al. [59]. Table 1 shows the distribution of the surveyed clnical data-driven works by task and by methodology. Figure 3 is shows ML categories represented across the data-driven CDSS papers.

Table 1. Overview of Clinical Data-Driven Approaches

Method family	Typical data	Common tasks	Evaluation	Representative refs
Linear / Regularized models (Logistic, Cox, LASSO)	Tabular EHR (labs, vitals, scores)	Risk stratification, prognosis, triage	AUC, calibration, decision curves	[48], [53], [60]
Tree ensembles (RF, GBM, XGBoost)	Tabular EHR; engineered features	Prediction, imputation, feature ranking	AUC, PPV@k, SHAP summaries	[53], [59], [60]
Deep learning – CNNs	Imaging (CT, MRI, X-ray)	Automated diagnosis, triage, workflow prioritization	AUC, AUCPR, sensitivity/specificity	[31], [59], [69]
Deep learning – RNNs/LSTMs	ICU waveforms, bedside monitors	Temporal acuity, sepsis early-warning	AUC, AUCPR, calibration	[53], [59], [60]
Transformers & multimodal DL	Imaging + labs + text	Integrated prediction, precision health	AUC, calibration, clinical utility	[59], [60], [63]
Reinforcement learning	Temporal EHR, ICU streams	Sequential therapy optimization	Off-policy estimators, counterfactual evaluation	[61]

Natural language processing (NLP)	Clinical notes, discharge summaries	Feature extraction, phenotyping, risk prediction	AUC, F1, downstream model performance	[63], [65]
Patient-similarity / metric learning	EHR similarity matrices	Mortality prediction, personalization	AUROC, calibration	[42]
Federated learning	Distributed hospital datasets	Risk prediction without data sharing	Federated AUC, convergence metrics	[57]
Synthetic data augmentation	Tabular/textual health records	External validation, method development	Fidelity, utility, privacy metrics	[70], [71]

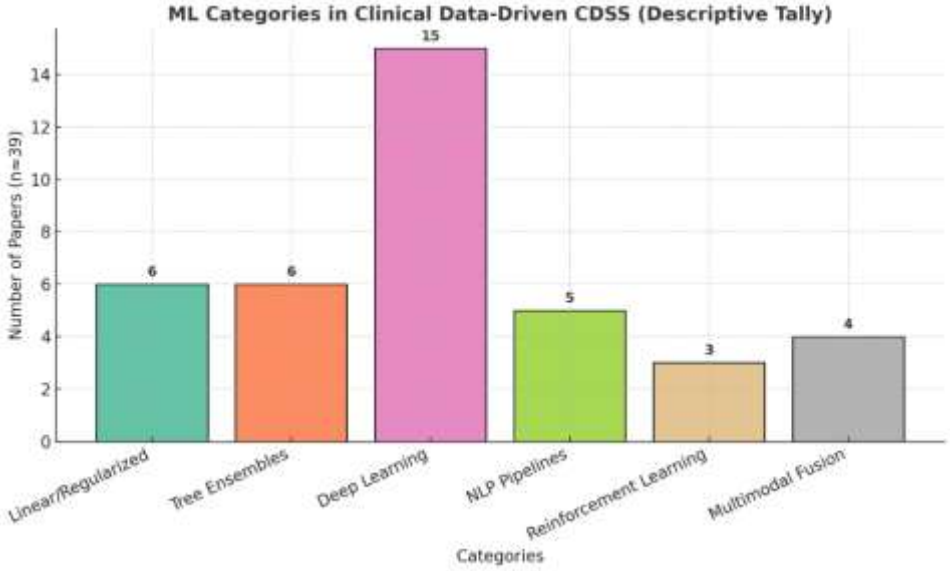

Figure 3. ML categories represented across the data-driven CDS papers (descriptive tally; n=39).

3.2 Rule-based decision support (16 papers; includes 5 hybrid)

Knowledge-based CDS remains essential wherever high-quality, codified medical knowledge exists (guidelines, care pathways, dosing rules, pharmacogenomic panels). Systems include production rule engines, computer-interpretable guidelines (CIGs), Bayesian/probabilistic structures, and case-based reasoning; common targets are medication management, diagnostic test ordering, and chronic-disease protocols [51, 44, 47, 52, 75]. When designed well, these tools reliably improve process measures—appropriate prescribing, monitoring, and test utilization—especially when advice is delivered automatically within the clinician's workflow, is patient-specific, and is framed as a recommendation rather than a passive assessment [32, 43, 45]. Earlier syntheses converged on similar success factors and documented consistent gains in process adherence with variable effects on clinical outcomes [35, 36].

Two persistent challenges are alert fatigue and maintenance burden. Poor signal-to-noise ratios—excessive or poorly targeted alerts—drive overrides and erode trust; human-factors principles for interface design and alert governance mitigate this [58]. Organizational barriers (change management, training, alignment with local pathways) also constrain impact; qualitative implementation work catalogs these hurdles and suggests staged adoption frameworks [46]. Even so, rule-based CDS excels where safety-critical constraints and explicit medical logic are required (e.g., drug–drug interactions, renal dosing, genotype-guided therapy), with pharmacogenomics CDS exemplifying how curated knowledge can be incorporated into real-time decisions [47, 52]. Five knowledge-based systems in our set embed data-driven modules, yielding hybrid designs (subsection 3.3). Table 2 shows the distribution of the surveyed knowledge(rule)-based works by task and by methodology.

Table 2. Rule-Based Clinical Decision Support

Knowledge base	Clinical domain	Delivery pattern	Key results	Representative refs
CIGs / pathways	Acute & chronic care	In-EHR prompts; order sets	Improved process adherence	[32], [43]

Drug–drug/condition rules	Medication safety	Inline prescribing alerts	Reduced prescribing errors; alert fatigue risk	[52], [58]
Pharmacogenomics rules	Genotype-guided therapy	Active genotype-aware alerts	More appropriate dosing/selection	[47], [52]
Bayesian/case-based	Diagnostic support	On-demand reasoning	Variable diagnostic gains; usability sensitive	[51], [75]

3.3 Hybrid approaches (5 papers)

Hybrid CCDS fuses learned models with encoded expert knowledge to combine accuracy with transparency and safety constraints. Architectural patterns include: (i) ML risk scores that gate guideline recommendations; (ii) knowledge-informed models where rules/ontologies define features, priors, or constraints; and (iii) explainable wrappers that translate model outputs into rule-grounded rationales and contraindication checks [53], [59], [68], [76].

Five anchor hybrids illustrate these patterns: (1) Moja et al. [38]—EHR-linked CDS combining structured rule triggers with predictive components at scale; (2) Roshanov et al. [45]—meta-regression identifying effectiveness features including hybrid designs and point-of-care recommendations; (3) Caballero-Ruíz et al. [44]—gestational-diabetes CDS pairing diet rules with ML to detect insulin needs; (4) Solares et al. [53]—hybrid EHR frameworks mixing alerts and deep models; (5) Kline et al. [59]—multimodal ML in precision health integrating structured rules, ML, imaging, and text. DECIDE-AI guidance maps naturally to hybrids, which must demonstrate human-factors fit and robustness of model–rule interaction prior to trials [40, 41]. Table 3 shows the distribution of the surveyed Hybrid works by task and by methodology. Figure 4 shows the Conceptual overlap between data-driven and rule-based CDS highlighting the hybrid intersection (n=5).

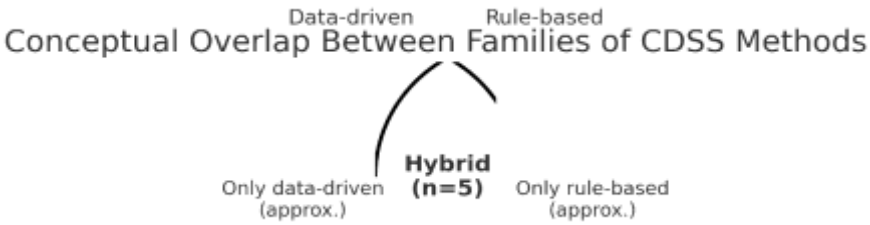

Figure 4. Conceptual overlap between data-driven and rule-based CDS highlighting the hybrid intersection (n=5).

Table 3. Hybrid CCDS: Integration Strategy and Evaluation

Study	Clinical domain	Integration strategy	Evaluation highlights	Ref
Moja et al., 2014	EHR-linked services (multi-domain)	Rule triggers + predictive components	Meta-analysis: modest process gains; heterogeneity	[9]
Roshanov et al., 2013	Multiple CDS trials	Rules + predictive/statistical methods	Meta-regression: point-of-care recommendations matter	[16]
Caballero-Ruíz et al., 2017	Gestational diabetes	Diet rules + ML for insulin need detection	Improved personalization vs. rules alone	[15]
Solares et al., 2020	EHR deep-learning frameworks	Rule alerts + DL models	Calibration & workflow compatibility emphasized	[24]

Kline et al., 2022	Precision health (multimodal)	Rules + ML + imaging + text	Context-aware recommendations; modality fusion	[30]

Distribution of Clinical Data-driven Decision Support System studies in shown in Figure 5.

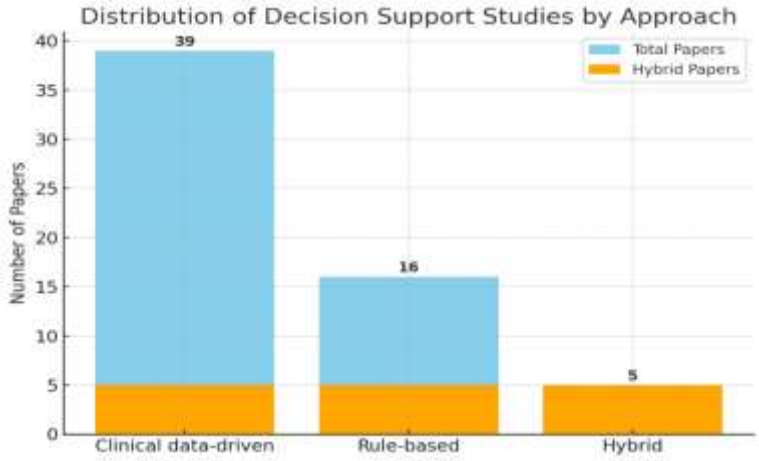

Figure 5 Distribution of Clinical Data-driven Decision Support System studies

3.4 Comparative synthesis

Distribution: 39/50 (78%) primarily data-driven; 16/50 (32%) rule-based; 5/50 (10%) hybrids (overlap with the other two families). Data-driven systems dominate prediction and triage, especially with large heterogeneous datasets [53, 59, 60, 69]; however, consistent patient-outcome gains are uncommon without strong implementation design [30, 35, 38]. Rule-based systems deliver explainability and safety-constraint enforcement, reliably improving process adherence when tightly integrated with workflow [32, 45, 47, 51, 52, 58]. Hybrids increasingly balance these strengths—leveraging learned sensitivity while preserving rule-grounded specificity and clinician-legible rationales [37, 44, 53, 59, 68, 76], [15]. Adoption depends on usability, transparency, local pathway alignment, and perceived value; barriers include alert fatigue, maintenance costs, and distrust of opaque models [46, 58, 65, 79]. Learning-health-system practices and rigorous reporting (e.g., DECIDE-AI) are central to trustworthy deployment [40, 41, 73, 74]. Figure 6 shows the *Distribution of approaches across the corpus (overlapping categories: totals exceed 100%).*

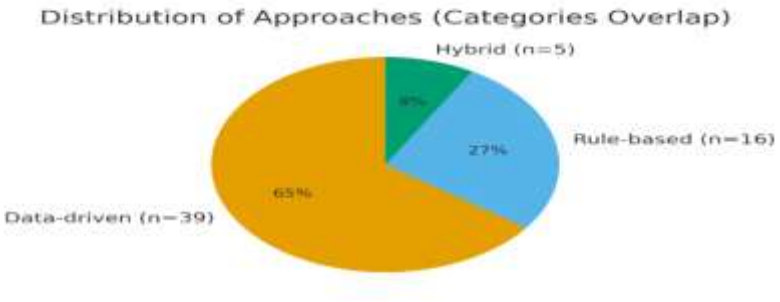

Figure 6. Distribution of approaches across the corpus (overlapping categories: totals exceed 100%).

4. DISCUSSION

The evidence base for clinical decision support systems (CDSS) has grown substantially, showing consistent, albeit modest, improvements in processes of care. Numerous systematic reviews and meta-analyses confirm that CDSS interventions enhance guideline adherence, optimize diagnostic test ordering, and improve prescribing safety [1] [2] [3] [4] [5] [7] [9] [17] [20] [29] [30] [34] [35] [36] [37] [43] [45]. The strength of evidence in favor of

process-level improvements is high, supported by multiple trials across acute, chronic, and preventive care settings [16] [21] [32] [54] [62]. However, the effects on patient outcomes remain smaller and more variable, with studies reporting inconsistent improvements in morbidity, mortality, or quality-of-life endpoints [3] [4] [5] [17] [34] [35] [36] [42]. This divergence underscores a central challenge: while CDSS standardize and improve processes, translating these into patient-centered benefits requires more than algorithms alone.

Data-driven CDSS, particularly those incorporating machine learning (ML), deep learning, and multimodal fusion, have demonstrated significant advances in predictive accuracy and personalization [6] [8] [10] [11] [12] [15] [18] [19] [31] [39] [48] [50] [53] [59] [60] [64] [69]. Applications range from sepsis mortality prediction [53] [69], antimicrobial therapy optimization [17], and oncology decision support [15], to multimodal models integrating imaging, text, and laboratory data [12] [18] [59]. These systems consistently outperform rule-based methods in internal validations, yet their deployment in clinical workflows faces barriers such as lack of transparency [10] [19] [65] [68], difficulties in integration [23] [24] [46] [58], and challenges of generalizability across settings [12] [53] [71]. Emerging paradigms like federated learning [57], reinforcement learning [61], and explainable AI (XAI) [23] [66] [68] [76] are proposed to address these issues, but real-world evaluations remain scarce.

Rule-based systems remain essential in domains with codified medical knowledge, such as pharmacogenomics, drug–drug interaction alerts, and guideline adherence [32] [43] [45] [47] [51] [52] [75]. These systems provide transparency and reliability, improving prescribing safety and monitoring [43] [47] [52]. However, their limitations include rigidity, maintenance burden, and alert fatigue [32] [46] [58]. Despite these challenges, their interpretability ensures continued use, particularly where safety and standardization are critical.

Hybrid systems aim to integrate the strengths of both paradigms. By combining predictive modeling with knowledge-based logic, hybrid CDSS can deliver accuracy while preserving interpretability [15] [24] [38] [44] [53] [59]. Examples include gestational diabetes management systems that combine dietary rules with ML to predict insulin needs [44], or oncology frameworks that merge multimodal predictions with safety rules [15]. Meta-analyses suggest that such designs offer modest but meaningful process gains [9] [16] [38], though rigorous validation is still needed.

Ethical, legal, and social issues (ELSI) increasingly shape the discourse on CDSS. Concerns about bias [6] [65] [66] [72], privacy [18] [57] [71], transparency [23] [66] [72], and accountability [10] [23] [72] have led to calls for regulatory frameworks and governance models [40] [41] [73] [74]. Without robust oversight, CDSS risk perpetuating inequities, eroding trust, and undermining patient safety. Explainable AI is widely viewed as critical for clinician acceptance [23] [66] [68] [76], yet evidence of its effectiveness in practice remains limited. Moreover, user studies emphasize that trust, usability, and alignment with clinical workflows are decisive factors in adoption [19] [23] [24] [46] [58] [79].

The future of CDSS lies at the intersection of technological sophistication and socio-technical integration. Advances in ML, deep learning, and data fusion have already expanded predictive capabilities [11] [12] [15] [50] [53] [59], while user-centered design, interdisciplinary collaboration, and rigorous real-world trials will be necessary to achieve sustained clinical impact [19] [40] [41] [73] [79]. To move beyond modest process improvements toward measurable patient outcome gains, research must prioritize generalizability, explainability, and integration into diverse healthcare contexts, including low- and middle-income countries [71]. Interdisciplinary efforts bridging data science, clinical practice, ethics, and health policy are essential to realize the full potential of CDSS as safe, effective, and equitable tools for modern healthcare.

Table 4 Key Themes in CDSS Evidence, Strength, and Representative References

Theme	Evidence Strength	Key Findings	Representative References
Process improvements (guideline adherence, test ordering, prescribing)	Strong	Consistent across multiple systematic reviews and meta-analyses	[1], [2], [3], [4], [5], [7], [9], [17], [20], [29], [30], [32], [34], [35], [36], [37], [43], [45], [52], [62]
Patient outcomes (mortality, morbidity, QoL)	Moderate	Limited and inconsistent effects; modest improvements in some contexts	[3], [4], [5], [17], [34], [35], [36], [42], [43], [69]
Data-driven CDSS (ML, DL, multimodal)	Strong for prediction;	High internal performance; barriers in explainability, generalizability, workflow	[6], [8], [10], [11], [12], [15], [18], [19], [31], [39], [48], [50],

	moderate for outcomes		[53], [59], [60], [64], [65], [68], [69], [71]
Rule-based CDSS	Strong for safety and reliability	Effective in pharmacogenomics, dosing, guideline adherence; alert fatigue common	[32], [43], [45], [47], [51], [52], [58], [75]
Hybrid CDSS	Emerging evidence	Combine accuracy with interpretability; early trials show modest process gains	[9], [15], [16], [24], [38], [44], [53], [59]
Implementation barriers	Strong	Workflow disruption, alert fatigue, training gaps, data quality issues	[23], [24], [25], [26], [29], [32], [46], [58]
Explainability & Trust (XAI)	Moderate	Critical for clinician acceptance, but limited real-world evidence	[8], [10], [19], [23], [65], [66], [68], [76], [79]
Ethical, legal, social issues	Moderate	Bias, accountability, data protection; need for governance frameworks	[6], [10], [23], [40], [41], [65], [66], [72], [73], [74]

5. CONCLUSION

Recent evidence confirms that clinical decision support systems (CDSS) deliver consistent improvements in care processes, though their direct impact on patient outcomes remains modest [1-5], [17], [34–36]. Data-driven approaches, particularly those using machine learning and multimodal data, show great promise for personalization and predictive accuracy [6], [10]–[15], [53], [59], [69]. However, their limited transparency, generalizability, and integration into workflows continue to constrain clinical adoption [19], [23], [24], [46], [58]. Rule-based systems remain reliable where interpretability and safety are paramount, yet they lack adaptability to complex scenarios [32], [43], [45], [47].

The synergy of hybrid systems, integrating the predictive power of data-driven models with the transparency of rule-based frameworks, represents a promising pathway forward [9], [15], [24], [38], [44]. Such designs can help address explainability, interoperability, and user trust, which are increasingly recognized as essential for responsible deployment [40], [41], [66], [72], [73].

In line with international recommendations, the full potential of CDSS will likely be realized through hybrid approaches that combine data-driven and knowledge-based methods, supported by robust governance and real-world validation. These strategies can ensure CDSS evolve into transparent, equitable, and clinically effective tools that augment medical decision-making and improve healthcare outcomes worldwide

5.1 Research Gap

Table 5: Heatmap of research coverage by topic and study attribute.

Topic/Outcome	Acute Care	Chronic Disease	Drug Management	Diagnostic Test Ordering	Multimodal Data Fusion
Process Improvement	7	8	6	5	2
Patient Outcomes	3	4	2	1	1
Implementation Barriers	4	3	2	1	GAP
Explainability/XAI	1	1	GAP	GAP	GAP
Ethical/Legal Issues	1	1	1	GAP	GAP

5.2 Open Research Questions

Table 6: Key open research questions and their significance for future work.

Question	Why
How can CDSS be designed to maximize patient outcome improvements, not just process adherence?	Most studies show process gains, but patient outcomes remain inconsistent; understanding this gap is crucial for clinical impact.

What are the most effective strategies for integrating explainable AI into CDSS to enhance clinician trust and adoption?	Lack of explainability is a major barrier; user-centered XAI could improve acceptance and safe use in practice.
How can CDSS be validated and deployed in diverse, real-world healthcare settings, including low- and middle-income countries?	Most research is from high-income settings; broader validation is needed for global health equity and generalizability.

In summary, while clinical data-driven decision support systems have advanced significantly, their full potential will only be realized through rigorous real-world validation, user-centered design, and proactive attention to ethical, legal, and social challenges.

REFERENCES

[1] Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. *NPJ digital medicine*, *3*(1), 17.
[2] Khalifa, M., Albadawy, M., & Iqbal, U. (2024). RETRACTED: Advancing clinical decision support: The role of artificial intelligence across six domains.
[3] Kwan, J. L., Lo, L., Ferguson, J., Goldberg, H., Diaz-Martinez, J. P., Tomlinson, G., ... & Shojania, K. G. (2020). Computerised clinical decision support systems and absolute improvements in care: meta-analysis of controlled clinical trials. *Bmj*, *370*.
[4] Bright, T. J., Wong, A., Dhurjati, R., Bristow, E., Bastian, L., Coeytaux, R. R., ... & Lobach, D. (2012). Effect of clinical decision-support systems: a systematic review. *Annals of internal medicine*, *157*(1), 29-43.
[5] Dhar, S. K., Navyav, K., Seth, K., Sharma, D., Singh, S. K., & Patil, S. (2024). Enhancing Clinical Decision Support Systems with Big Data and AI in Medical Informatics. In *Seminars in Medical Writing and Education* (Vol. 3, pp. 503-503). AG Editor (Argentina).
[6] Ouanes, K., & Farhah, N. (2024). Effectiveness of artificial intelligence (AI) in clinical decision support systems and care delivery. *Journal of medical systems*, *48*(1), 74.
[7] Elhaddad, M., & Hamam, S. (2024). AI-driven clinical decision support systems: an ongoing pursuit of potential. *Cureus*, *16*(4).
[8] ATUL, R. B. (2025). Transforming healthcare delivery: AI-powered clinical decision support systems. *INTERNATIONAL JOURNAL*, *11*(1), 339-347.
[9] Basile, L. J., Carbonara, N., Pellegrino, R., & Panniello, U. (2023). Business intelligence in the healthcare industry: The utilization of a data-driven approach to support clinical decision making. *Technovation*, *120*, 102482.
[10] Evans, R., Bryant, L., Russell, G., & Absolom, K. (2025). Clinical Trust in Data-Driven Decision Support Tools: Qualitative Interview Study. In *Intelligent Health Systems–From Technology to Data and Knowledge* (pp. 410-411). IOS Press.
[11] Moreira, M. W., Rodrigues, J. J., Korotaev, V., Al-Muhtadi, J., & Kumar, N. (2019). A comprehensive review on smart decision support systems for health care. *IEEE Systems Journal*, *13*(3), 3536-3545.
[12] Susanto, A. P., Lyell, D., Widyantoro, B., Berkovsky, S., & Magrabi, F. (2023). Effects of machine learning-based clinical decision support systems on decision-making, care delivery, and patient outcomes: a scoping review. *Journal of the American Medical Informatics Association*, *30*(12), 2050-2063.
[13] Montani, S., & Striani, M. (2019). Artificial intelligence in clinical decision support: a focused literature survey. *Yearbook of medical informatics*, *28*(01), 120-127.
[14] Reis, W. C., Bonetti, A. F., Bottacin, W. E., Reis Jr, A. S., Souza, T. T., Pontarolo, R., ... & Fernandez-Llimos, F. (2017). Impact on process results of clinical decision support systems (CDSSs) applied to medication use: overview of systematic reviews. *Pharmacy Practice (Granada)*, *15*(4).
[15] Chang, J. S., Kim, H., Baek, E. S., Choi, J. E., Lim, J. S., Kim, J. S., & Shin, S. J. (2025). Continuous multimodal data supply chain and expandable clinical decision support for oncology. *npj Digital Medicine*, *8*(1), 128.
[16] Song, M., & Liu, D. (2025). International visualization analysis of research hotspots and development trends in the study of clinical decision support systems utilizing CiteSpace. *Frontiers in Medicine*, *12*, 1546611.
[17] Müller, L., Srinivasan, A., Abeles, S. R., Rajagopal, A., Torriani, F. J., & Aronoff-Spencer, E. (2021). A risk-based clinical decision support system for patient-specific antimicrobial therapy (iBiogram): design and retrospective analysis. *Journal of medical Internet research*, *23*(12), e23571.
[18] Shang, Y., Tian, Y., Lyu, K., Zhou, T., Zhang, P., Chen, J., & Li, J. (2024). Electronic health record–oriented knowledge graph system for collaborative clinical decision support using multicenter fragmented medical data: design and application study. *Journal of Medical Internet Research*, *26*, e54263.
[19] Evans, R. P., Bryant, L. D., Russell, G., & Absolom, K. (2024). Trust and acceptability of data-driven clinical recommendations in everyday practice: A scoping review. *International Journal of Medical Informatics*, *183*, 105342.
[20] Horsky, J., Aarts, J., Verheul, L., Seger, D. L., van der Sijs, H., & Bates, D. W. (2017). Clinical reasoning in the context of active decision support during medication prescribing. *International journal of medical informatics*, *97*, 1-11.
[21] Schummers, L., Himes, K. P., Bodnar, L. M., & Hutcheon, J. A. (2016). Predictor characteristics necessary for building a clinically useful risk prediction model: a simulation study. *BMC medical research methodology*, *16*(1), 123.
[22] Yoo, I., Alafaireet, P., Marinov, M., Pena-Hernandez, K., Gopidi, R., Chang, J. F., & Hua, L. (2012). Data mining in healthcare and biomedicine: a survey of the literature. *Journal of medical systems*, *36*(4), 2431-2448.
[23] Feinleib, D. (2014). *Big data bootcamp: What managers need to know to profit from the big data revolution*. Apress.

[24] Rubiano, S. M. M., & Garcia, J. A. D. (2016). Analysis of data mining techniques for constructing a predictive model for academic performance. *IEEE Latin America Transactions*, *14*(6), 2783-2788.
[25] Power, D. J. (2008). Decision support systems: a historical overview. In *Handbook on decision support systems 1: Basic themes* (pp. 121-140). Berlin, Heidelberg: Springer Berlin Heidelberg.
[26] Power, D. J. (2008). Understanding data-driven decision support systems. *Information Systems Management*, *25*(2), 149-154.
[27] Xu, B., Da Xu, L., Cai, H., Xie, C., Hu, J., & Bu, F. (2014). Ubiquitous data accessing method in IoT-based information system for emergency medical services. *IEEE Transactions on Industrial informatics*, *10*(2), 1578-1586.
[28] Sunyaev, A., & Chornyi, D. (2012). Supporting chronic disease care quality: design and implementation of a health service and its integration with electronic health records. *Journal of Data and Information Quality (JDIQ)*, *3*(2), 1-21.
[29] Kilsdonk, E., Peute, L. W., & Jaspers, M. W. (2017). Factors influencing implementation success of guideline-based clinical decision support systems: a systematic review and gaps analysis. *International journal of medical informatics*, *98*, 56-64.
[30] Kwan, J., Lo, L., Ferguson, J., Goldberg, H., Díaz-Martínez, J., Tomlinson, G., Grimshaw, J., & Shojania, K. (2020). Computerised clinical decision support systems and absolute improvements in care: meta-analysis of controlled clinical trials. *The BMJ*, 370. https://doi.org/10.1136/bmj.m3216.
[31] Moreira, M., Rodrigues, J., Korotaev, V., Al-Muhtadi, J., & Kumar, N. (2019). A Comprehensive Review on Smart Decision Support Systems for Health Care. *IEEE Systems Journal*, 13, 3536-3545. https://doi.org/10.1109/JSYST.2018.2890121.
[32] Van De Velde, S., Heselmans, A., Delvaux, N., Brandt, L., Marco-Ruiz, L., Spitaels, D., Cloetens, H., Kortteisto, T., Roshanov, P., Kunnamo, I., Aertgeerts, B., Vandvik, P., & Flottorp, S. (2018). A systematic review of trials evaluating success factors of interventions with computerised clinical decision support. *Implementation Science : IS*, 13. https://doi.org/10.1186/s13012-018-0790-1.
[33] Giordano, C., Brennan, M., Mohamed, B., Rashidi, P., Modave, F., & Tighe, P. (2021). Accessing Artificial Intelligence for Clinical Decision-Making. *Frontiers in Digital Health*, 3. https://doi.org/10.3389/fdgth.2021.645232.
[34] Roshanov, P., Misra, S., Gerstein, H., Garg, A., Sebaldt, R., Mackay, J., Weise-Kelly, L., Navarro, T., Wilczynski, N., Haynes, R., & Team, T. (2011). Computerized clinical decision support systems for chronic disease management: A decision-maker-researcher partnership systematic review. *Implementation Science : IS*, 6, 92 - 92. https://doi.org/10.1186/1748-5908-6-92.
[35] Jaspers, M., Smeulers, M., Vermeulen, H., & Peute, L. (2011). Effects of clinical decision-support systems on practitioner performance and patient outcomes: a synthesis of high-quality systematic review findings. *Journal of the American Medical Informatics Association : JAMIA*, 18 3, 327-34 . https://doi.org/10.1136/amiajnl-2011-000094.
[36] Haynes, R., Wilczynski, N., & Team, T. (2010). Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: Methods of a decision-maker-researcher partnership systematic review. *Implementation Science : IS*, 5, 12 - 12. https://doi.org/10.1186/1748-5908-5-12.
[37] Fernandes, M., Vieira, S., Leite, F., Palos, C., Finkelstein, S., & Sousa, J. (2020). Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: a Review. *Artificial intelligence in medicine*, 102, 101762 . https://doi.org/10.1016/j.artmed.2019.101762.
[38] Moja, L., Kwag, K., Lytras, T., Bertizzolo, L., Brandt, L., Pecoraro, V., Rigon, G., Vaona, A., Ruggiero, F., Mangia, M., Iorio, A., Kunnamo, I., & Bonovas, S. (2014). Effectiveness of computerized decision support systems linked to electronic health records: a systematic review and meta-analysis.. *American journal of public health*, 104 12, e12-22 . https://doi.org/10.2105/AJPH.2014.302164.
[39] Peiffer-Smadja, N., Rawson, T., Ahmad, R., Buchard, A., Pantelis, G., Lescure, F., Birgand, G., & Holmes, A. (2020). Machine learning for clinical decision support in infectious diseases: A narrative review of current applications.. *Clinical microbiology and infection : the official publication of the European Society of Clinical Microbiology and Infectious Diseases*. https://doi.org/10.1016/j.cmi.2019.09.009.
[40] Vasey, B., Nagendran, M., Campbell, B., Clifton, D., Collins, G., Denaxas, S., Denniston, A., Faes, L., Geerts, B., Ibrahim, M., Liu, X., Mateen, B., Mathur, P., Mccradden, M., Morgan, L., Ordish, J., Rogers, C., Saria, S., Ting, D., Watkinson, P., Weber, W., Wheatstone, P., & McCulloch, P. (2022). Reporting guideline for the early stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *The BMJ*, 377. https://doi.org/10.1136/bmj-2022-070904.
[41] Vasey, B., Nagendran, M., Campbell, B., Clifton, D., Collins, G., Denaxas, S., Denniston, A., Faes, L., Geerts, B., Ibrahim, M., Liu, X., Mateen, B., Mathur, P., Mccradden, M., Morgan, L., Ordish, J., Rogers, C., Saria, S., Ting, D., Watkinson, P., Weber, W., Wheatstone, P., & McCulloch, P. (2022). Reporting guideline for the early-stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *Nature Medicine*, 28, 924 - 933. https://doi.org/10.1038/s41591-022-01772-9.
[42] Lee, J., Maslove, D., & Dubin, J. (2015). Personalized Mortality Prediction Driven by Electronic Medical Data and a Patient Similarity Metric. *PLoS ONE*, 10. https://doi.org/10.1371/journal.pone.0127428.
[43] Sahota, N., Lloyd, R., Ramakrishna, A., Mackay, J., Prorok, J., Weise-Kelly, L., Navarro, T., Wilczynski, N., & Haynes, B. (2011). Computerized clinical decision support systems for acute care management: A decision-maker-researcher partnership systematic review of effects on process of care and patient outcomes. *Implementation Science : IS*, 6, 91 - 91. https://doi.org/10.1186/1748-5908-6-91.
[44] Caballero-Ruíz, E., García-Sáez, G., Rigla, M., Villaplana, M., Pons, B., & Hernando, M. (2017). A web-based clinical decision support system for gestational diabetes: Automatic diet prescription and detection of insulin needs. *International journal of medical informatics*, 102, 35-49 . https://doi.org/10.1016/j.ijmedinf.2017.02.014.
[45] Roshanov, P., Fernandes, N., Wilczynski, J., Hemens, B., You, J., You, J., Handler, S., Nieuwlaat, R., Nieuwlaat, R., Souza, N., Beyene, J., Beyene, J., Spall, H., Spall, H., Garg, A., Garg, A., & Haynes, R. (2013). Features of effective computerised clinical decision support systems: meta-regression of 162 randomised trials. *BMJ : British Medical Journal*, 346. https://doi.org/10.1136/bmj.f657.
[46] Liberati, E., Ruggiero, F., Galuppo, L., Gorli, M., González-Lorenzo, M., Maraldi, M., Ruggieri, P., Friz, H., Scaratti, G., Kwag, K., Vespignani, R., & Moja, L. (2017). What hinders the uptake of computerized decision support systems in hospitals? A qualitative study and framework for implementation. *Implementation Science : IS*, 12. https://doi.org/10.1186/s13012-017-0644-2.

[47] Bell, G., Crews, K., Wilkinson, M., Haidar, C., Hicks, J., Baker, D., Kornegay, N., Yang, W., Cross, S., Howard, S., Freimuth, R., Evans, W., Broeckel, U., Relling, M., & Hoffman, J. (2013). Development and use of active clinical decision support for preemptive pharmacogenomics. *Journal of the American Medical Informatics Association : JAMIA*, 21, e93 - e99. https://doi.org/10.1136/amiajnl-2013-001993.

[48] Shamout, F., Zhu, T., & Clifton, D. (2020). Machine Learning for Clinical Outcome Prediction. *IEEE Reviews in Biomedical Engineering*, 14, 116-126. https://doi.org/10.1109/RBME.2020.3007816.

[49] Alowais, S., Alghamdi, S., Alsuhebany, N., Alqahtani, T., Alshaya, A., Almohareb, S., Aldairem, A., Alrashed, M., Saleh, K., Badreldin, H., Yami, M., Harbi, S., & Albekairy, A. (2023). Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC Medical Education*, 23. https://doi.org/10.1186/s12909-023-04698-z.

[50] Mohsen, F., Ali, H., Hajj, N., & Shah, Z. (2022). Artificial intelligence-based methods for fusion of electronic health records and imaging data. *Scientific Reports*, 12. https://doi.org/10.1038/s41598-022-22514-4.

[51] Wright, A., Sittig, D., Ash, J., Feblowitz, J., Meltzer, S., McMullen, C., Guappone, K., Carpenter, J., Richardson, J., Simonaitis, L., Evans, R., Nichol, W., & Middleton, B. (2011). Development and evaluation of a comprehensive clinical decision support taxonomy: comparison of front-end tools in commercial and internally developed electronic health record systems. *Journal of the American Medical Informatics Association : JAMIA*, 18 3, 232-42 . https://doi.org/10.1136/amiajnl-2011-000113.

[52] Hemens, B., Holbrook, A., Tonkin, M., Mackay, J., Weise-Kelly, L., Navarro, T., Wilczynski, N., Haynes, B., & Team, T. (2011). Computerized clinical decision support systems for drug prescribing and management: A decision-maker-researcher partnership systematic review. *Implementation Science : IS*, 6, 89 - 89. https://doi.org/10.1186/1748-5908-6-89.

[53] Solares, J., Raimondi, F., Zhu, Y., Rahimian, F., Canoy, D., Tran, J., Gomes, A., Payberah, A., Zottoli, M., Nazarzadeh, M., Conrad, N., Rahimi, K., & Khorshidi, G. (2020). Deep learning for electronic health records: A comparative review of multiple deep neural architectures. *Journal of biomedical informatics*, 101, 103337 . https://doi.org/10.1016/j.jbi.2019.103337.

[54] P. Roshanov et al. "Can computerized clinical decision support systems improve practitioners' diagnostic test ordering behavior? A decision-maker-researcher partnership systematic review." *Implementation Science : IS*, 6 (2011): 88 - 88. https://doi.org/10.1186/1748-5908-6-88.

[55] Silvana Secinaro et al. "The role of artificial intelligence in healthcare: a structured literature review." *BMC Medical Informatics and Decision Making*, 21 (2021). https://doi.org/10.1186/s12911-021-01488-9.

[56] Borja Martínez-Pérez et al. "Mobile Clinical Decision Support Systems and Applications: A Literature and Commercial Review." *Journal of Medical Systems*, 38 (2013): 1-10. https://doi.org/10.1007/s10916-013-0004-y.

[57] Rodolfo Stoffel Antunes et al. "Federated Learning for Healthcare: Systematic Review and Architecture Proposal." *ACM Transactions on Intelligent Systems and Technology (TIST)*, 13 (2022): 1 - 23. https://doi.org/10.1145/3501813.

[58] J. Horsky et al. "Interface design principles for usable decision support: A targeted review of best practices for clinical prescribing interventions." *Journal of biomedical informatics*, 45 6 (2012): 1202-16 . https://doi.org/10.1016/j.jbi.2012.09.002.

[59] Adrienne S. Kline et al. "Multimodal machine learning in precision health: A scoping review." *NPJ Digital Medicine*, 5 (2022). https://doi.org/10.1038/s41746-022-00712-8.

[60] Ying Yu et al. "Clinical big data and deep learning: Applications, challenges, and future outlooks." *Big Data Min. Anal.*, 2 (2019): 288-305. https://doi.org/10.26599/BDMA.2019.9020007.

[61] Siqi Liu et al. "Reinforcement Learning for Clinical Decision Support in Critical Care: Comprehensive Review." *Journal of Medical Internet Research*, 22 (2020). https://doi.org/10.2196/18477.

[62] M. Sousa et al. "Decision-Making based on Big Data Analytics for People Management in Healthcare Organizations." *Journal of Medical Systems*, 43 (2019). https://doi.org/10.1007/s10916-019-1419-x.

[63] Elias Hossain et al. "Natural Language Processing in Electronic Health Records in relation to healthcare decision-making: A systematic review." *Computers in biology and medicine*, 155 (2023): 106649 . https://doi.org/10.1016/j.compbiomed.2023.106649.

[64] Saima Safdar et al. "Machine learning based decision support systems (DSS) for heart disease diagnosis: a review." *Artificial Intelligence Review*, 50 (2017): 597 - 623. https://doi.org/10.1007/s10462-017-9552-8.

[65] Michael Wornow et al. "The shaky foundations of large language models and foundation models for electronic health records." *NPJ Digital Medicine*, 6 (2023). https://doi.org/10.1038/s41746-023-00879-8.

[66] Anto Čartolovni et al. "Ethical, legal, and social considerations of AI-based medical decision-support tools: A scoping review." *International journal of medical informatics*, 161 (2022): 104738 . https://doi.org/10.1016/j.ijmedinf.2022.104738.

[67] Kornelia M. Batko et al. "The use of Big Data Analytics in healthcare." *Journal of Big Data*, 9 (2022). https://doi.org/10.1186/s40537-021-00553-4.

[68] H. Loh et al. "Application of explainable artificial intelligence for healthcare: A systematic review of the last decade (2011-2022)." *Computer methods and programs in biomedicine*, 226 (2022): 107161 . https://doi.org/10.1016/j.cmpb.2022.107161.

[69] M. M. R. Andrew Taylor et al. "Prediction of In-hospital Mortality in Emergency Department Patients With Sepsis: A Local Big Data-Driven, Machine Learning Approach.." *Academic emergency medicine : official journal of the Society for Academic Emergency Medicine*, 23 3 (2016): 269-78 . https://doi.org/10.1111/acem.12876.

[70] Mikel Hernandez et al. "Synthetic data generation for tabular health records: A systematic review." *Neurocomputing*, 493 (2022): 28-45. https://doi.org/10.1016/j.neucom.2022.04.053.

[71] Fang Liu et al. "Real-world data: a brief review of the methods, applications, challenges and opportunities." *BMC Medical Research Methodology*, 22 (2022). https://doi.org/10.1186/s12874-022-01768-6.

[72] Ciro Mennella et al. "Ethical and regulatory challenges of AI technologies in healthcare: A narrative review." *Heliyon*, 10 (2024). https://doi.org/10.1016/j.heliyon.2024.e26297.

[73] J. Enticott et al. "Learning health systems using data to drive healthcare improvement and impact: a systematic review." *BMC Health Services Research*, 21 (2021). https://doi.org/10.1186/s12913-021-06215-8.

[74] A. D. de Hond et al. "Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review." *NPJ Digital Medicine*, 5 (2022). https://doi.org/10.1038/s41746-021-00549-7.
[75] K. Wagholikar et al. "Modeling Paradigms for Medical Diagnostic Decision Support: A Survey and Future Directions." *Journal of Medical Systems*, 36 (2012): 3029-3049. https://doi.org/10.1007/s10916-011-9780-4.
[76] Flavio Di Martino et al. "Explainable AI for clinical and remote health applications: a survey on tabular and time series data." *Artificial Intelligence Review*, 56 (2022): 5261 - 5315. https://doi.org/10.1007/s10462-022-10304-3.
[77] Pouyan Esmaeilzadeh et al. "Use of AI-based tools for healthcare purposes: a survey study from consumers' perspectives." *BMC Medical Informatics and Decision Making*, 20 (2020). https://doi.org/10.1186/s12911-020-01191-1.
[78] T. Loftus et al. "Artificial Intelligence and Surgical Decision-Making.." *JAMA surgery* (2019). https://doi.org/10.1001/jamasurg.2019.4917.
[79] S. Lambert et al. "An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals." *NPJ Digital Medicine*, 6 (2023). https://doi.org/10.1038/s41746-023-00852-5.
[80] Rao, A., Pang, M., Kim, J., Kamineni, M., Lie, W., Prasad, A., Landman, A., Dreyer, K., & Succi, M. Assessing the Utility of ChatGPT Throughout the Entire Clinical Workflow: Development and Usability Study. *Journal of Medical Internet Research.* 2023; 25. https://doi.org/10.2196/48659
[81] An, Q., Rahman, S., Zhou, J., & Kang, J. A Comprehensive Review on Machine Learning in Healthcare Industry: Classification, Restrictions, Opportunities and Challenges. *Sensors (Basel, Switzerland).* 2023; 23. https://doi.org/10.3390/s23094178
[82] Busnatu, Ş., Niculescu, A., Bolocan, A., Petrescu, G., Păduraru, D., Năstasă, I., Lupuşoru, M., Geantă, M., Andronic, O., Grumezescu, A., & Martins, H. Clinical Applications of Artificial Intelligence—An Updated Overview. *Journal of Clinical Medicine.* 2022; 11. https://doi.org/10.3390/jcm11082265
[83] Plana, D., Shung, D., Grimshaw, A., Saraf, A., Sung, J., & Kann, B. Randomized Clinical Trials of Machine Learning Interventions in Health Care. *JAMA Network Open.* 2022; 5. https://doi.org/10.1001/ jamanetworkopen.2022.33946
[84] Buchlak, Q., Esmaili, N., Leveque, J., Farrokhi, F., Bennett, C., Piccardi, M., & Sethi, R. Machine learning applications to clinical decision support in neurosurgery: an artificial intelligence augmented systematic review. *Neurosurgical Review.* 2019; 43. https://doi.org/10.1007/s10143-019-01163-8
[85] Kumar, Y., Koul, A., Singla, R., & Ijaz, M. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. *Journal of Ambient Intelligence and Humanized Computing.* 2022; 14. https://doi.org/10.1007/s12652-021-03612-z
[86] Zhang, K., Liu, X., Shen, J., Li, Z., Sang, Y., Wu, X., Zha, Y., Liang, W., Wang, C., Wang, K., Ye, L., Gao, M., Zhou, Z., Li, L., Wang, J., Yang, Z., Cai, H., Xu, J., Yang, L., Cai, W., Xu, W., Wu, S., Zhang, W., Jiang, S., Zheng, L., Zhang, X., Wang, L., Lu, L., Li, J., Yin, H., Wang, W., Li, O., Zhang, C., Liang, L., Wu, T., Deng, R., Wei, K., Zhou, Y., Chen, T., Lau, J., Fok, M., He, J., Lin, T., Li, W., & Wang, G. Clinically Applicable AI System for Accurate Diagnosis, Quantitative Measurements, and Prognosis of COVID-19 Pneumonia Using Computed Tomography. *Cell.* 2020; 182. https://doi.org/10.1016/j.cell.2020.08.029
[87] Ahmed, S., Alam, M., Afrin, S., Rafa, S., Rafa, N., & Gandomi, A. Insights into Internet of Medical Things (IoMT): Data fusion, security issues and potential solutions. *Inf. Fusion.* 2023; 102. https://doi.org/10. 1016/j.inffus.2023.102060
[88] Khanra, S., Dhir, A., Islam, N., & Mäntymäki, M. Big data analytics in healthcare: a systematic literature review. *Enterprise Information Systems.* 2020; 14. https://doi.org/10.1080/17517575.2020.1812005
[89] Pareek, A., Seyyedi, S., Banerjee, I., & Lungren, M. Fusion of medical imaging and electronic health records using deep learning: a systematic review and implementation guidelines. *NPJ Digital Medicine.* 2020; 3. https://doi.org/10.1038/s41746-020-00341-z