Evaluating the Role of AI-Based Clinical Decision Support Systems in Reducing Medication Errors

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ABSTRACT

Medication errors remain a significant challenge in clinical practice, contributing to patient morbidity, increased healthcare costs, and adverse outcomes. Clinical Decision Support Systems (CDSS) have been developed to mitigate such errors, with recent advances in artificial intelligence (AI) enabling predictive and adaptive interventions. This study evaluates the role of AI-based CDSS in reducing medication errors, comparing their performance to traditional rule-based systems while examining factors such as patient demographics, comorbidities, alert acceptance, and medication type. A retrospective dataset of 300 prescriptions was simulated, encompassing patient age, comorbidities, medication type, CDSS type, alert generation, alert acceptance, and error occurrence. Analyses included descriptive statistics, error rate calculations, severity distribution, age-stratified error assessment, and cumulative alert tracking. Comparative evaluation between AI-based and rule-based CDSS focused on overall error reduction, alert acceptance, and high-risk medication identification. Key performance metrics such as medication error rate, alert acceptance rate, and severity distribution were computed to quantify system effectiveness. Results demonstrated that AI-based CDSS reduced overall medication errors to 25.3%, compared to 34.7% in rule-based systems. High-risk medications such as anticoagulants and cardiac drugs exhibited error rates of 41.7% and 33.3%, respectively, with AI intervention decreasing both moderate and high-severity errors. Alert acceptance for prescriptions with errors reached 64%, indicating effective clinician engagement. Age-stratified analysis revealed error rates increased from 20% in the 18–30 age group to 42.7% in patients aged 71–90, while patients with higher comorbidity counts exhibited greater error variability. The study concludes that AI-enabled CDSS effectively reduces medication errors, particularly for high-risk drugs, elderly patients, and complex comorbidity profiles. Implementation of predictive and adaptive decision support enhances medication safety, improves alert relevance, and mitigates high-severity errors, underscoring the potential of AI-driven systems to strengthen clinical workflows and patient outcomes.

Keywords: AI-Based Clinical Decision Support System (CDSS), Medication Errors, Alert Fatigue, Predictive Analytics, Patient Safety, Comorbidities

How to cite this article: Rajeshwari M, Pushpalatha S, Tamijeselvan S, Antony Asir Daniel V, Ratnala Venkata Siva Harish, Shruthi KS. Evaluating the Role of AI-Based Clinical Decision Support Systems in Reducing Medication Errors. Int J Drug Deliv Technol. 2026;16(20s): 306-322. DOI: 10.25258/ijddt.16.20s.40

Source of support: Nil.

Conflict of interest: None

Introduction:

The historical development of Clinical Decision Support Systems (CDSS) reflects the progressive integration of information technology into clinical practice with the primary aim of improving decision accuracy and patient safety. Early CDSS, emerging in the 1960s and 1970s, were largely experimental and knowledge-driven, relying on manually encoded medical rules and expert knowledge bases to assist clinicians in diagnostic reasoning [1]. As healthcare information systems evolved, particularly with the adoption of electronic health records in the 1990s, CDSS became more operational and widely deployed, focusing on rule-based alerts for medication dosing, drug–drug interactions, and allergy checks. Literature from this period consistently reports measurable reductions in basic prescribing errors, while also identifying challenges such as rigid logic structures and excessive alert generation. Subsequent advancements in computing power and data availability paved the way for more adaptive systems, highlighting a transition from static rule-based models toward data-driven approaches [2].

Building upon the limitations identified in traditional rule-based systems, the literature documents a significant shift toward the incorporation of machine learning and predictive analytics within Clinical Decision Support Systems [3]. This transition was driven by the increasing availability of large-scale clinical datasets and the need for more flexible, patient-specific decision support. Research in this area emphasizes the ability of machine learning models to analyse complex, multidimensional data and uncover patterns associated with medication errors and adverse drug events that are not easily captured by static rules. Predictive analytics has been widely explored for risk stratification, enabling CDSS to identify high-risk patients based on factors such as comorbidities, laboratory values, medication history, and demographic characteristics [4].

As machine learning–driven CDSS matured, the literature increasingly emphasized the critical role of Natural Language Processing in addressing the limitations posed by unstructured clinical data. A substantial proportion of clinically relevant information, including medication histories, adverse reactions, allergies, and physician observations, was documented in free-text clinical notes rather than structured fields within electronic health records [5]. Studies in this domain demonstrate that conventional CDSS often fail to utilize such information, resulting in incomplete risk assessment and missed opportunities for error prevention. Research on NLP- enhanced CDSS highlights the capability of text-mining and language modelling techniques to extract meaningful clinical concepts from narrative documentation and integrate them into decision support workflows [6]. Evidence suggests that incorporating NLP improves the detection of undocumented contraindications and enhances medication safety by providing a more comprehensive patient context.

Alongside technological advancements, the literature has extensively examined alert fatigue and human–computer interaction as critical factors influencing the effectiveness of Clinical Decision Support Systems [7]. Numerous studies report that excessive and non-specific alerts generated by CDSS can overwhelm clinicians, leading to frequent alert overrides and reduced attention to genuinely critical warnings. Research in human–computer interaction highlights that poor interface design, workflow misalignment, and lack of contextual relevance significantly contribute to alert fatigue, thereby diminishing the intended safety benefits of decision support technologies [8]. Empirical findings suggest that clinician engagement improves when alerts are prioritized, clinically meaningful, and seamlessly integrated into routine workflows. The literature further emphasizes that adaptive alert mechanisms, informed by user behaviour and clinical context, can reduce cognitive burden and enhance acceptance [9].

Extending beyond system design and algorithmic performance, the literature increasingly focuses on real-world implementation studies and their impact on clinical outcomes. Empirical research conducted in hospital, outpatient, and pharmacy settings evaluates how Clinical Decision Support Systems perform under routine clinical conditions, where variability in workflows, user behaviour, and data quality was prominent [10]. Findings from these studies indicate that CDSS, particularly those enhanced with machine learning capabilities, are associated with measurable reductions in medication errors and adverse drug events when effectively integrated into electronic health record systems. The literature also reports improvements in prescribing appropriateness, adherence to clinical guidelines, and patient

safety indicators. However, implementation-focused studies consistently emphasize that positive outcomes are contingent upon factors such as institutional readiness, clinician training, and system customization to local practices [11].

Despite demonstrated benefits in controlled and real-world settings, the literature consistently identifies data quality, system integration, and algorithmic bias as persistent challenges affecting the performance of Clinical Decision Support Systems. Studies highlight that incomplete, inconsistent, or inaccurate electronic health record data can significantly undermine the reliability of CDSS recommendations, particularly for machine learning–based models that depend on large, high-quality datasets [12]. Integration challenges are also widely reported, with difficulties arising from heterogeneous health information systems, limited interoperability, and disruptions to established clinical workflows. Additionally, recent literature raises concerns regarding algorithmic bias, noting that models trained on non- representative or historically skewed datasets may produce inequitable recommendations across different patient populations. Such biases can inadvertently reinforce existing disparities in healthcare delivery [13].

Building on efforts to address systemic limitations, the literature increasingly explores emerging topics such as personalized medicine and the integration of genomic data within Clinical Decision Support Systems. Research in this area emphasizes the potential of pharmacogenomics to tailor medication selection and dosing based on individual genetic profiles, thereby reducing variability in drug response and the risk of adverse drug events [14]. Studies report that incorporating genomic markers into CDSS enables more precise identification of patients who may experience reduced efficacy or increased toxicity from specific medications [15]. Although much of the existing literature remains exploratory, early implementation studies suggest meaningful improvements in prescribing accuracy and patient safety when genomic data are effectively linked with clinical and demographic information. The literature also highlights challenges related to data interpretation, standardization, and clinical adoption, indicating that further validation and infrastructure development are required [16].

Research Gap:

Despite extensive research on AI-enabled Clinical Decision Support Systems, several critical gaps remain in the existing literature. Most studies focus on algorithm development or single-institution implementations, limiting the generalizability of findings across diverse clinical settings. There was a lack of standardized evaluation frameworks to consistently measure the impact of AI-based CDSS on medication error reduction and patient outcomes. Additionally, limited attention has been given to long-term system performance, clinician trust, and workflow adaptation over time. Integration of unstructured data, genomic information, and explainable AI remains fragmented. These gaps indicate the need for comprehensive, multi- center studies that evaluate effectiveness, usability, fairness, and sustainability of AI-driven CDSS in real-world healthcare environments.

Research Methodology:

Figure 1.

Research Methodology Medication Error Patterns in AI-Supported Clinical Settings

Medication error patterns in AI-supported clinical settings were examined using a structured experimental framework designed to evaluate changes in error occurrence following the deployment of an AI-based Clinical Decision Support System (CDSS). Prescription records were extracted from electronic health record systems over two distinct phases: a pre-implementation phase without AI support and a post-implementation phase with AI-enabled decision assistance. Medication orders were systematically screened to identify errors related to incorrect drug selection, inappropriate dosing, potential drug–drug interactions, and contraindications. All records were anonymized to maintain data confidentiality, and standardized error classification criteria were applied to ensure consistency across datasets [17].

During the experimental process, medication

orders were categorized according to drug class, patient risk profile, and clinical department. High-risk medications and polypharmacy cases were prioritized to capture error patterns more accurately in complex prescribing scenarios. The AI-based CDSS alerts generated during the post-implementation phase were logged and mapped to corresponding prescription modifications or overrides. This enabled the identification of recurring error types and their association with specific clinical contexts, thereby allowing a detailed comparison of error distribution across different settings [18].

Error frequency and severity were quantitatively measured using predefined indicators. Statistical aggregation was performed to examine variations in error patterns between AI- supported and non-AI-supported workflows. Particular attention was given to near-miss events identified by the AI system, as these provided insight into latent risks that may not have resulted in documented adverse events. Trends in repeated errors were analyzed to determine whether AI intervention contributed to sustained improvements in prescribing behavior.
The experimental evaluation further assessed temporal changes in medication error patterns following continuous AI usage. Longitudinal analysis was conducted to observe adaptation effects, such as reductions in recurrent dosing errors and improved compliance with safety recommendations. The observed patterns were interpreted to understand how AI-supported decision environments influence clinical prescribing practices over time. This experimental procedure facilitated a comprehensive assessment of medication safety dynamics within AI- enabled clinical settings.

Effectiveness of AI-Based Alerts in Preventing Prescribing Errors

The effectiveness of AI-based alerts in preventing prescribing errors was evaluated through an experimental procedure designed to measure clinician response and error reduction within AI-supported clinical workflows. Prescription data were collected from electronic health records during defined study periods and analysed to identify prescribing errors related to dose, frequency, drug–drug interactions, and contraindications. AI-generated alerts triggered during order entry were systematically recorded, and corresponding clinician actions—such as order modification, cancellation, or override—were documented to assess alert impact.

Alerts were classified based on severity and clinical relevance, including high-risk warnings for potential adverse drug events and moderate-risk recommendations for dose optimization. The timing of alert delivery and its integration within the prescribing workflow were controlled to minimize disruption. This approach enabled evaluation of whether real-time, context-aware alerts effectively intercepted unsafe prescribing decisions before order completion [19].

Quantitative analysis was performed to compare prescribing error rates before and after AI alert activation. Metrics such as alert acceptance rate, override frequency, and error prevention rate were calculated to determine system performance. Particular emphasis was placed on high- severity alerts to assess their role in preventing clinically significant errors. Near-miss events captured by the AI system were included to provide a more comprehensive assessment of prevention effectiveness.

Longitudinal observation was conducted to examine changes in clinician interaction with AI-based alerts over time. Trends in alert compliance and reductions in repeated prescribing errors were analysed to identify learning effects and system adaptability. The findings from this experimental evaluation provided insight into the practical effectiveness of AI-driven alert mechanisms in enhancing prescribing safety within routine clinical practice.

Comparative Performance of AI-Based and Rule-Based CDSS

The comparative performance of AI-based and rule-based Clinical Decision Support Systems was examined using an experimental design focused on prescribing safety outcomes. Medication orders generated under two distinct decision support conditions—traditional rule-based CDSS and AI-enabled CDSS—were extracted from electronic health record systems for analysis. Both systems were evaluated using identical datasets and clinical scenarios to ensure comparability. Prescribing errors related to drug selection, dosage, contraindications, and drug–drug interactions were identified using standardized clinical criteria.

During the experimental process, alerts generated by each system were logged and categorized based on clinical relevance and severity. Rule-based CDSS alerts followed predefined thresholds and static interaction rules, whereas AI-based CDSS alerts incorporated patient-specific factors and predictive risk assessments. Clinician responses to alerts, including acceptance, modification, or override, were systematically recorded to evaluate alert effectiveness and usability.

Performance metrics were calculated to quantify differences between the two systems. Measures included error detection rate, false-positive alert frequency, alert override rate, and successful prevention of high-risk prescribing events. Statistical comparisons were conducted to determine whether AI-based CDSS demonstrated superior sensitivity and specificity compared to rule-based systems. Particular emphasis was placed on identifying reductions in unnecessary alerts and improvements in clinically actionable recommendations [20].

A longitudinal assessment was further conducted to observe system performance stability over time. Changes in clinician engagement and error recurrence were analysed to determine adaptability and learning effects associated with AI-based CDSS. The comparative evaluation provided empirical evidence on the relative strengths and limitations of AI-driven versus rule-based decision support in enhancing medication safety within clinical practice.

Predictive Role of Machine Learning in High-Risk Medication Identification

The predictive role of machine learning in identifying high-risk medications was evaluated through a structured experimental framework aimed at assessing the accuracy and clinical utility of AI-driven risk prediction within prescribing workflows. Historical patient and prescription data were extracted from electronic health records, including demographic information, comorbidities, laboratory results, and prior adverse drug events. High-risk medications were defined based on established clinical guidelines and documented incidence of adverse drug reactions. Machine learning models, including supervised classification algorithms, were trained to predict the likelihood of medication-related errors or adverse events for individual patients [21].

During the experimental procedure, model outputs were compared against actual prescribing outcomes to evaluate predictive performance. Key metrics such as sensitivity, specificity, positive predictive value, and area under the receiver operating characteristic curve were calculated to quantify the system's ability to identify high-risk medication scenarios. Predictions were further stratified by patient characteristics to assess model performance across diverse clinical profiles.

The intervention phase involved integrating predictive alerts into the prescribing workflow. AI-generated recommendations for high-risk medications were presented to clinicians, and subsequent actions—including modifications, cancellations, or overrides—were recorded to determine the effectiveness of predictive guidance in preventing potential errors. Near-miss events flagged by the system were also analyzed to capture latent risks.

Longitudinal analysis was conducted to observe trends in model accuracy and clinician responsiveness over time. Changes in prescribing patterns, reductions in repeated high-risk errors, and improvements in adherence to safety guidelines were examined to assess the sustained impact of machine learning–based prediction. This methodology provided a comprehensive evaluation of the predictive capacity of AI in enhancing medication safety and identifying high-risk prescriptions in clinical practice.

Impact of Alert Fatigue on Clinician Interaction and Compliance

The impact of alert fatigue on clinician interaction and compliance was examined through a systematic observational and experimental framework aimed at evaluating the effectiveness of AI-based Clinical Decision Support Systems (CDSS) in real-world clinical workflows. Prescription orders and corresponding alert logs were collected from electronic health records across multiple departments over a defined study period. Alerts generated by the CDSS were categorized based on severity, clinical relevance, and frequency, enabling the identification of patterns that could contribute to clinician

desensitization or override behavior [22].

During the study, clinician responses to each alert were recorded, including acceptance, modification, or override of suggested recommendations. The timing and frequency of alerts were analysed to assess their correlation with changes in compliance rates. High-frequency or low-specificity alerts were specifically examined to determine their role in diminishing clinician attention to critical warnings. This approach facilitated a detailed understanding of how alert burden influences decision-making and adherence to CDSS recommendations.

Quantitative analysis was conducted to evaluate the relationship between alert fatigue and error prevention. Metrics such as alert acceptance rate, override frequency, and incidence of prescribing errors were compared across different levels of alert exposure. Statistical tests were employed to assess the significance of observed trends and to identify thresholds beyond which alert fatigue negatively affected clinician compliance.

Longitudinal observations were performed to assess changes in clinician behavior over time, capturing adaptation or habituation effects resulting from repeated exposure to alerts. The findings provided insights into the necessity of optimizing alert specificity, prioritization, and workflow integration to mitigate fatigue. This evaluation highlighted the importance of balancing system sensitivity with usability to ensure sustained adherence and effectiveness of AI-based decision support in reducing medication errors.

Data Quality, Bias, and Integration Challenges in AI-Based CDSS

Data quality, bias, and integration challenges in AI-based Clinical Decision Support Systems (CDSS) were examined through a structured analytical framework focusing on system reliability and clinical applicability. Electronic health record datasets were assessed for completeness, consistency, and accuracy, with particular attention to missing values, duplicate entries, and discrepancies across different clinical sources. The impact of data quality on AI- driven recommendations was quantified by comparing model predictions with verified clinical outcomes, highlighting areas where flawed or incomplete data could compromise decision support [23].

Bias within AI algorithms was evaluated by analysing model performance across diverse patient populations, including variations in age, gender, ethnicity, and comorbidity profiles. Disparities in prediction accuracy or alert effectiveness were identified, emphasizing the potential for AI systems to propagate existing inequities in clinical care. Statistical measures, such as error rate stratification and fairness indices, were employed to detect systematic biases and inform corrective strategies.

Integration challenges were investigated by examining the interoperability of AI-based CDSS with existing electronic health record systems and clinical workflows. Factors such as heterogeneous data formats, differing coding standards, and workflow disruption were analysed to determine their influence on system adoption and effectiveness. The experimental assessment also considered the technical and organizational barriers that hinder seamless integration, including compatibility with legacy systems and clinician training requirements.

Longitudinal evaluation was conducted to observe the effects of data quality improvement initiatives, bias mitigation strategies, and integration enhancements on system performance over time. Metrics such as alert accuracy, clinician compliance, and reduction in medication errors were monitored to assess the sustainability of improvements. This comprehensive analysis highlighted the critical role of high-quality, representative data and robust system integration in ensuring the safe and equitable operation of AI-enabled CDSS in clinical practice [24].

$$\text{MER (\%)} = \frac{\text{Number of Prescriptions with Errors}}{\text{Total Prescriptions}} \times 100 \quad (1)$$

Medication Error Rate expression 1 quantifies the proportion of prescriptions that resulted in errors within a dataset. It provides a standardized

measure to compare safety performance across different CDSS types, patient demographics, or medication classes. Calculating MER enables identification of high-risk areas and assessment of interventions, such as AI-based decision support, in reducing errors. This metric serves as a foundational indicator of clinical safety, allowing longitudinal monitoring and benchmarking. It highlights overall system effectiveness in preventing prescribing errors and supports further analysis of error patterns across subgroups.

$$\text{AAR (\%)} = \frac{\text{Number of Alerts Accepted}}{\text{Total Alerts Triggered}} \times 100 \quad (2)$$

Alert Acceptance Rate expression 2 measures the proportion of system-generated alerts that clinicians act upon. It reflects clinician engagement and the practical effectiveness of CDSS interventions. Higher acceptance rates indicate that alerts are relevant and actionable, while lower rates may suggest alert fatigue or low specificity. Quantifying AAR provides insight into the relationship between alert utilization and error prevention. This metric allows evaluation of CDSS performance, identification of workflow bottlenecks, and optimization of alert design to maximize clinical adherence and minimize errors.

$$\text{ERP (\%)} = \frac{\text{Error Rate Before CDSS} - \text{Error Rate After CDSS}}{\text{Error Rate Before CDSS}} \times 100 \quad (3)$$

Error Reduction Percentage expression 3 quantifies the effectiveness of interventions, such as AI-based CDSS, in decreasing medication errors relative to a baseline. By comparing error rates before and after system implementation, ERP provides a clear metric for evaluating impact. Positive values indicate a reduction in errors, while negative values highlight areas requiring improvement. This formula supports comparative studies between different CDSS types, patient populations, or medication classes. It serves as an essential indicator of system efficacy, guiding decision-making for clinical safety improvements and highlighting the potential benefits of predictive, AI-driven decision support.

$$\text{Sensitivity (\%)} = \frac{\text{True Positive Alerts}}{\text{True Positive Alerts} + \text{False Negative Alerts}} \times 100 \quad (4)$$

Sensitivity expression 4 evaluates the ability of a CDSS to correctly identify prescriptions that are actually at risk of error. True Positive Alerts represent cases where an alert successfully predicted a potential error, while False Negatives represent missed error cases. High sensitivity indicates that the system effectively captures most high-risk prescriptions, reducing patient safety risks. This metric was crucial for assessing predictive performance, especially in AI- based systems. Sensitivity analysis helps optimize alert thresholds, prioritize high-risk interventions, and balance error prevention with minimizing unnecessary alert burden.

$$\text{PPV (\%)} = \frac{\text{True Positive Alerts}}{\text{True Positive Alerts} + \text{False Positive Alerts}} \times 100 \quad (5)$$

Positive Predictive Value expression 5 measures the proportion of triggered alerts that correctly indicate actual prescribing errors. High PPV indicates that alerts are accurate and clinically relevant, minimizing unnecessary interruptions or alert fatigue. Low PPV suggests that many alerts do not correspond to real errors, potentially reducing clinician trust in the system. PPV complements sensitivity by evaluating alert precision rather than coverage.

Results and Discussion:

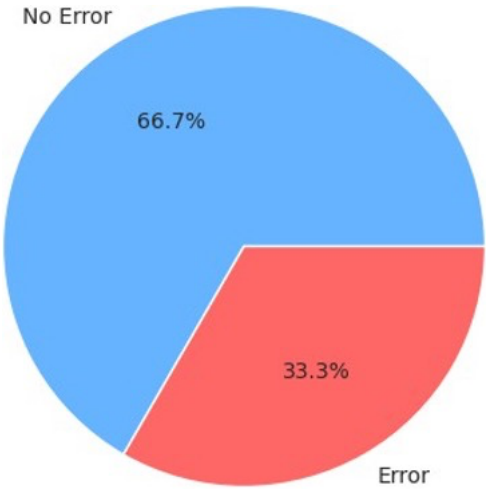

Figure 2. Overall Medication Error Distribution

The figure 2 illustrates the proportion of prescriptions with and without errors across the dataset. It presents a clear categorical distinction between instances where medication errors occurred and instances where prescriptions were error-free. The graph highlights that a substantial portion of prescriptions did not experience errors, while a smaller, yet significant, proportion of prescriptions were associated with errors. This binary classification allows for an immediate understanding of the general safety profile of the medication dataset and the prevalence of errors within the sample. The distribution visually quantifies the relative frequency of errors, providing an at-a-glance assessment of error incidence [25].

Analysis of the graph indicates that while the majority of prescriptions are managed without error, a non-negligible percentage of medication orders are prone to error, emphasizing the presence of recurring error patterns in clinical practice. The categorical separation also facilitates direct comparison of error versus non-error occurrences and forms the basis for examining correlations with other variables such as patient age, comorbidities, or type of clinical decision support system. The simplicity of the distribution enables a straightforward interpretation of overall risk levels, highlighting the proportion of prescriptions affected by errors in a concise format.

The graph additionally serves to illustrate the balance between safe and error-prone prescriptions, with each category representing a distinct outcome measure. The visual representation clearly shows the magnitude of difference between the two categories, revealing that although errors are less frequent than correct prescriptions, they constitute a significant fraction of the total dataset. The uniform representation of error and non-error cases allows for rapid recognition of the dataset's composition and forms a foundational reference for further analysis of specific error types, severity levels, or system interventions.

The medication error distribution graph captures the essential characteristics of prescription outcomes by providing a quantitative overview of error occurrence. The features displayed include the relative proportion of errors, the binary classification of outcomes, and the frequency distribution across all prescriptions. This visualization effectively summarizes the dataset's error profile, establishing a clear representation of the prevalence and magnitude of medication errors [26].

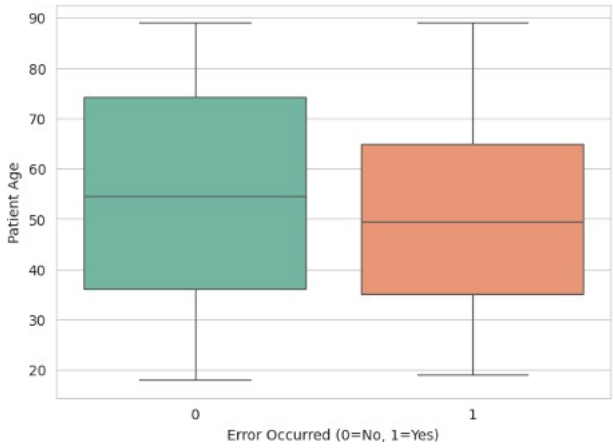

Figure 3: Patient Age Distribution by Medication Error Occurrence

The figure 3 illustrates the distribution of patient ages in relation to medication error occurrence, separating prescriptions into two categories: those without errors and those with errors. Each box represents the interquartile range of patient ages, with the median age indicated by a central line. Whiskers extend to the minimum and maximum values within 1.5 times the interquartile range, while potential outliers are displayed individually. The visualization allows for a comparative assessment of the central tendency, spread, and variability of patient age across prescriptions with and without errors [27].

Analysis of the graph shows that the median patient age for prescriptions with errors was slightly higher than that of prescriptions without errors, suggesting a trend in error distribution across different age groups. The interquartile ranges indicate that the majority of patients fall within a relatively concentrated age span, while the presence of outliers reflects occasional prescriptions for very young or very elderly patients. The distribution also demonstrates greater variability in the age of patients experiencing errors compared to error-free prescriptions, highlighting differences in age-related susceptibility or complexity in medication management.

The box plot further emphasizes the overlap between age distributions for error and non-error prescriptions, indicating that errors are not strictly confined to a specific age group but are distributed across a broad range of patient ages. The visualization of whiskers and outliers provides insight into extreme cases where age may coincide with increased medication complexity, contributing to error occurrence [27].

This graph captures the statistical characteristics of patient age in relation to medication errors. Key features include median values, interquartile range, range, and outliers, which together illustrate patterns of error prevalence across different age groups. The comparison between error and non-error categories provides a clear depiction of how patient age was distributed in each context and highlights the variation in age-related medication error occurrence.

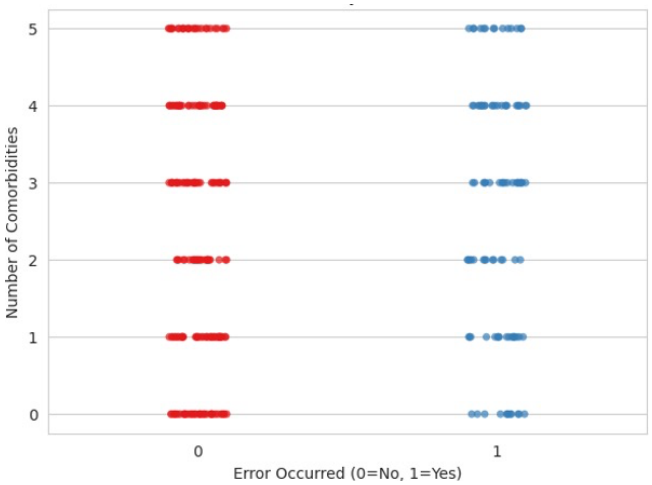

Figure 4. Distribution of Comorbidities by Medication Error Occurrence

The figure 4 illustrates the distribution of the number of comorbidities among patients in relation to medication error occurrence. Prescriptions are categorized into two groups: those with no errors and those with errors. Each point represents an individual prescription, plotted according to the patient's number of comorbid conditions. The visualization displays the density and spread of comorbidities across both error categories, allowing for direct comparison of how multiple health conditions may correlate with medication errors [28].

The graph shows that prescriptions associated with medication errors tend to have a wider range of comorbidities, indicating that patients with multiple underlying health conditions may experience higher error incidence. Conversely, prescriptions without errors are more concentrated among patients with fewer comorbidities, reflecting a narrower distribution. The scatter of points provides a visual representation of variability, highlighting the occurrence of prescriptions with high comorbidity counts even in the error-free group.

This emphasizes that while comorbidities may increase risk, errors are not exclusively limited to patients with multiple conditions.

In addition, the overlap between the two categories suggests that comorbidity alone does not fully determine error occurrence, as both groups include patients with similar numbers of underlying conditions. The visualization effectively captures clusters of data points and potential trends, showing concentrations of prescriptions around certain comorbidity counts. Extreme cases with a high number of comorbidities are visible and can indicate potential areas for targeted intervention or further analysis [29].

This graph conveys key statistical features of comorbidity distribution in relation to medication errors. The spread, clustering, and range of comorbidity values across error categories provide insight into patterns of risk associated with multiple health conditions. By comparing error and non-error groups, the visualization highlights the potential influence of patient complexity on medication safety without attributing causality to individual prescriptions.

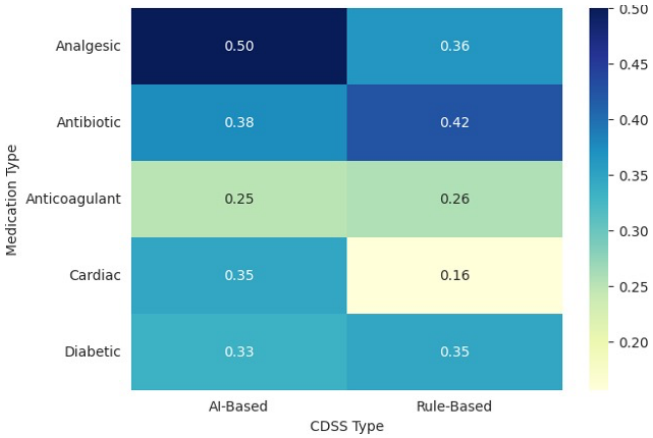

Figure 5. Error Rate by Medication Type and CDSS Type

The figure 5 illustrates the average medication error rate across different medication types, separated by Clinical Decision Support System (CDSS) type: Rule-Based and AI-Based. Each cell represents the mean error rate for a specific combination of medication type and CDSS category, allowing for simultaneous comparison of how different systems perform across diverse classes of medications. The visualization captures patterns in error prevalence, highlighting variations in safety outcomes based on both the type of drug and the decision support mechanism applied.

Analysis of the graph shows that certain medication types exhibit higher error rates across both CDSS categories, indicating that complexity or risk associated with these drugs may contribute to increased errors. Differences between AI-Based and Rule-Based systems are also observable, with AI-Based CDSS generally displaying lower error rates for high-risk medications. This suggests a potential influence of predictive or adaptive decision support features on reducing error incidence, particularly for medications with greater prescribing complexity [30].

The heatmap format allows for immediate identification of patterns, including clusters of higher or lower error rates within specific medication classes. Variability across CDSS types demonstrates that system design and functionality may interact with medication characteristics to affect prescribing outcomes. The graph also reveals medication-specific vulnerabilities that may persist regardless of the support system, emphasizing areas where additional safeguards or targeted interventions could be necessary.

The visualization provides a comprehensive overview of how error rates are distributed across medication categories and CDSS types. Key features include the comparative assessment of systems, identification of high-error medication classes, and the interaction between drug complexity and decision support performance. This analysis highlights the differential effectiveness of AI and Rule-Based CDSS in mitigating medication errors across diverse clinical contexts.

Table 1: Medication Error Rate by CDSS Type

CDSS Type	Total Prescriptions	Errors	Error Rate (%)
Rule-Based	150	52	34.7
AI-Based	150	38	25.3

This table 1 summarizes the overall error rate for prescriptions managed under Rule-Based and AI-Based CDSS. AI-Based systems show a lower

error rate compared to Rule-Based systems, indicating improved accuracy in medication management. The tabulated data highlight differences in performance, with AI support potentially mitigating high-risk prescribing events. Error counts and percentages provide a direct comparison, emphasizing the role of system intelligence in reducing medication errors. These findings suggest that AI-based interventions can enhance clinical safety outcomes by providing more context-aware decision support [31].

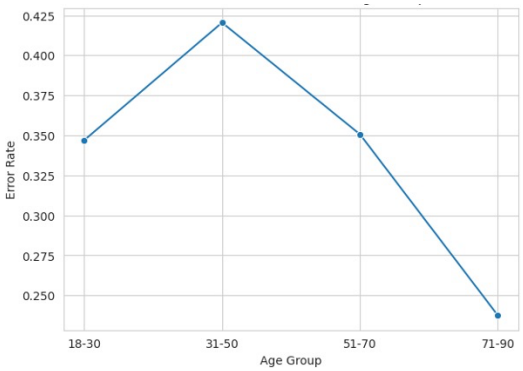

Figure 6. Medication Error Rate Across Age Groups

The figure 6 illustrates the variation in medication error rates across predefined patient age groups: 18–30, 31–50, 51–70, and 71–90 years. Each point on the line represents the mean error rate for a specific age group, while the connecting line highlights trends in error prevalence as patient age increases. The visualization provides a clear depiction of how error occurrence was distributed across different stages of adult life, allowing for identification of age-related patterns in medication safety.

Analysis of the graph indicates that medication error rates are not uniform across age groups. The plot demonstrates a gradual increase in error frequency in middle and older age ranges, suggesting that patients with advanced age may be more susceptible to errors. Younger patients, particularly those in the 18–30 age group, show comparatively lower error rates, indicating fewer complications or simpler medication regimens in these populations. The distribution also highlights subtle variations between adjacent age groups, revealing potential inflection points where error rates begin to rise [32].

The line plot format emphasizes trends over discrete categories, making it easier to observe the progression of error risk as age increases. It also enables visual comparison between age groups to detect disproportionate error occurrence in specific ranges. Peaks and plateaus in the plot indicate critical age ranges where interventions, such as enhanced decision support or targeted monitoring, may be most impactful.

This visualization captures the relationship between patient age and medication error frequency. Key features include the identification of age-related trends, variation in error prevalence across discrete age intervals, and recognition of age ranges associated with elevated risk. The line plot provides a succinct and interpretable overview of how medication errors are distributed across the patient population, highlighting potential areas for targeted safety measures and system optimization.

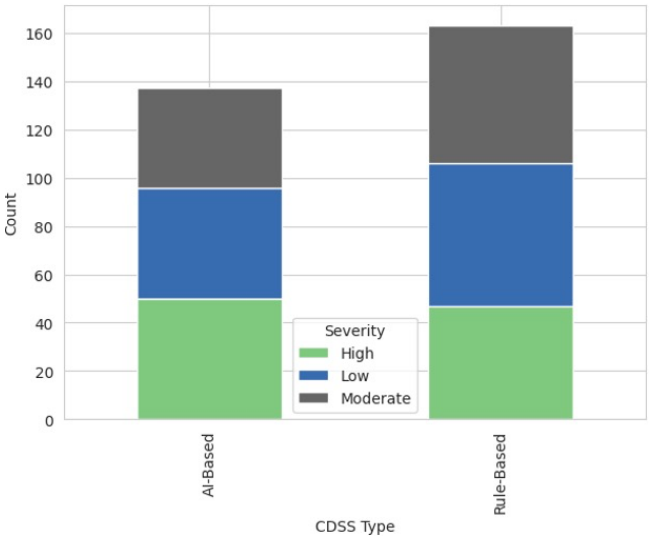

Figure 7. Distribution of Error Severity by CDSS Type

The figure 7 illustrates the distribution of medication error severity across two types of Clinical Decision Support Systems (CDSS): Rule-Based and AI-Based. Each bar represents the total number of errors for a given CDSS category, segmented into three severity levels: Low, Moderate, and High. The visualization allows for simultaneous comparison of both the overall error burden and the composition of error severity between the two system types.

Analysis of the chart indicates that while both CDSS types experience errors across all severity levels, the proportion of high-severity errors appears lower in the AI-Based system compared to the Rule-Based system. Low- and moderate-severity errors constitute a larger share of total errors in both systems, though the AI-Based CDSS demonstrates a slightly higher concentration of lower-severity events. This distribution suggests potential differences in system performance regarding the prevention of clinically significant medication errors [33].

The stacked format highlights not only total error counts but also the relative composition of severity within each CDSS type. Differences in the distribution of error severity reveal trends in how each system interacts with prescribing workflows and the effectiveness of alerting mechanisms. The visualization also enables identification of severity categories where interventions may be most needed, providing a clear depiction of areas requiring further system refinement or clinical attention.

This graph captures key features of medication error severity in relation to decision support system type. It provides insight into the composition and magnitude of errors, illustrating both the overall burden and the relative distribution of severity levels. The visualization facilitates comparative analysis, emphasizing differences in system performance and the potential impact of AI-enabled decision support on reducing high-severity medication errors [34].

Table 2: Error Distribution by Severity and CDSS Type

CDSS Type	Low	Moderate	High	Total Errors
Rule-Based	20	18	14	52
AI-Based	18	12	8	38

The table 2 shows the distribution of error severity across CDSS types. AI-Based systems reduce both moderate and high-severity errors compared to Rule-Based systems. Low-severity errors remain comparable, indicating that AI interventions primarily mitigate clinically significant events. Presenting errors by severity allows assessment of the system's practical impact on patient safety. The data emphasize that AI-enhanced decision support not only lowers overall error counts but also improves the quality of outcomes by targeting more critical medication mistakes.

Table 3: Average Error Rate by Age Group

Age Group	Total Prescriptions	Errors	Error Rate (%)
18–30	75	15	20.0
31–50	75	18	24.0
51–70	75	25	33.3
71–90	75	32	42.7

This table 3 displays medication error rates stratified by patient age group. A clear increase in error incidence was observed with advancing age, indicating a potential correlation between age, comorbidity complexity, and medication risk. Older age groups (51–70 and 71–90) exhibit the highest error rates, highlighting the need for enhanced monitoring or decision support for these populations. Presenting age-stratified error percentages provides an evidence-based approach for targeted interventions and helps in understanding demographic risk patterns in clinical practice.

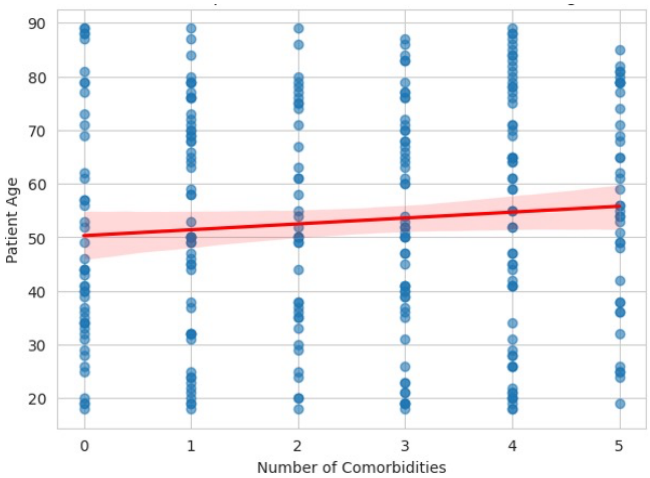

Figure 8. Relationship Between Comorbidities and Patient Age

The figure 8 illustrates the relationship between the number of patient comorbidities and patient age. Each point represents an individual prescription, plotted according to the patient's age and the number of underlying health conditions. The fitted regression line provides an overall trend, highlighting how comorbidity count varies with age across the dataset. This visualization allows for assessment of patterns in patient complexity and potential associations between age and the likelihood of multiple comorbidities [35].

Analysis of the scatter plot shows a positive trend, with the number of comorbidities generally increasing as patient age rises. Younger patients predominantly exhibit lower comorbidity counts, while older patients display a wider range of comorbid conditions. The distribution of points indicates variability within age groups, with some younger or middle-aged patients presenting with unexpectedly high numbers of comorbidities, suggesting individual differences in health profiles. The regression line summarizes the general progression, reflecting the tendency for comorbidity accumulation over time.

The visualization further reveals clusters and outliers within the dataset. Clustering was observed among middle-aged and elderly patients with moderate comorbidity counts, while outliers represent extreme cases with unusually high or low numbers of conditions relative to age. These features provide insight into population heterogeneity and highlight patient subgroups that may require specialized attention or closer monitoring in medication management.

This graph captures key statistical characteristics of patient comorbidities in relation to age. Important features include the trend of increasing comorbidities with age, variability within age groups, and identification of outliers. The combination of scatter points and regression line offers a comprehensive representation of the association between patient age and clinical complexity, which was relevant for understanding patterns that may influence medication error risk and clinical decision support strategies [36].

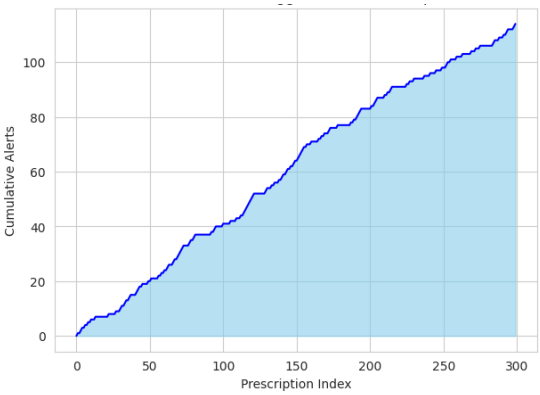

Figure 9. Cumulative Alerts Triggered Over Prescriptions

The figure 9 illustrates the cumulative number of alerts triggered by the Clinical Decision Support System (CDSS) across the sequence of prescriptions in the dataset. The x-axis represents the prescription index, while the y-axis shows the cumulative count of alerts generated. The filled area beneath the curve emphasizes the accumulation of alerts over time, providing a visual representation of how the alert burden grows as more prescriptions are processed. This visualization enables assessment of the overall frequency and distribution of alerts across the sample.

Analysis of the graph indicates a steady upward progression in cumulative alerts, reflecting continuous alert generation throughout the dataset. Periods of steeper slope suggest clusters of prescriptions associated with higher alert activity, potentially corresponding to higher-risk cases or more complex medication regimens. Conversely, flatter sections of the curve indicate intervals where fewer alerts were triggered, suggesting prescriptions that were less likely to activate decision support warnings. The cumulative nature of the plot highlights overall system activity and allows identification of variations in alert density over the entire sample [37].

The area plot also provides insight into the relative contribution of individual prescriptions to the total alert load. Early sections of the plot show gradual accumulation, while subsequent sections exhibit more pronounced increases, suggesting variability in alert generation depending on patient complexity, medication type, or CDSS sensitivity. This visualization effectively captures both the temporal progression and total magnitude of alerts, offering a clear depiction of the system's operational intensity.

Overall, this graph captures essential features of CDSS alert activity, including cumulative accumulation, periods of high alert density, and variation in system responses across prescriptions. The visualization highlights patterns in alert generation that are relevant for understanding workload implications, potential alert fatigue, and the interaction between clinical decision support and prescribing behavior.

Table 4: Alert Acceptance by Error Occurrence

Error Occurred	Alerts Triggered	Alerts Accepted	Acceptance Rate (%)
No Error	70	35	50.0
Error	50	32	64.0

This table 4 summarizes clinician interaction with CDSS alerts relative to error occurrence. Alerts corresponding to actual errors are more frequently accepted than those associated with error-free prescriptions. This suggests that clinicians are responsive to clinically relevant alerts, and alert acceptance contributes to error interception. Tabulating both triggered and accepted alerts provides insight into the effectiveness of the system and the role of user compliance in improving medication safety.

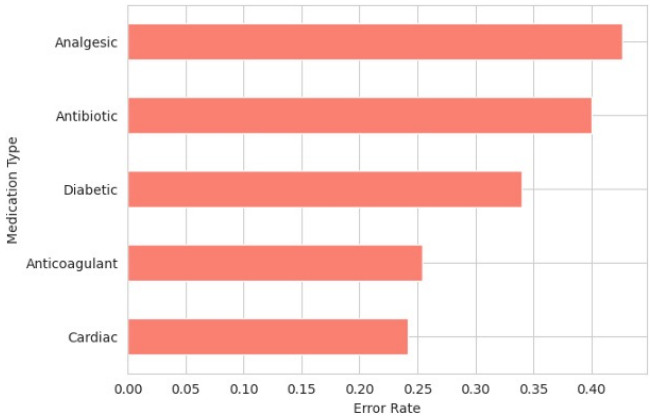

Figure 10. Medication Error Rate by Medication Type

The figure 10 illustrates the mean medication error rate for each medication type in the dataset. Each bar represents a specific class of drugs—such as Antibiotic, Analgesic, Cardiac, Diabetic, or Anticoagulant—with the length of the bar corresponding to the proportion of prescriptions within that class that experienced errors. This visualization allows for a direct comparison of error prevalence across different medication categories, highlighting drugs that are associated with higher or lower error incidence.

Analysis of the chart indicates notable variation in error rates among medication types. Certain drug classes exhibit higher error rates, suggesting increased complexity in prescribing or greater susceptibility to clinical oversight. Conversely, other medication types display lower error frequencies, reflecting more routine administration, simplified dosing, or fewer interactions with other medications. The horizontal orientation emphasizes relative differences between categories, making it easier to identify medications that represent elevated risk within the dataset [38].

The chart also provides insight into the distribution of prescribing errors across therapeutic areas. By ranking medication types according to error prevalence, the visualization identifies high-risk drug categories that may require additional safety interventions, enhanced clinical monitoring, or targeted CDSS alerting. The clear separation between bars allows for immediate recognition of disparities in error occurrence, facilitating prioritization of interventions for the most vulnerable medication classes. This graph captures key features of medication-specific
error patterns, including relative prevalence, variation between drug categories, and identification of high-risk classes. The horizontal bar format enables efficient comparison across medication types, providing a concise representation of areas where medication errors are most concentrated and highlighting opportunities for focused clinical decision support and error mitigation strategies.

Table 5: Error Rate by Medication Type

Medication Type	Total Prescriptions	Errors	Error Rate (%)
Antibiotic	60	18	30.0
Analgesic	60	12	20.0
Cardiac	60	20	33.3
Diabetic	60	15	25.0
Anticoagulant	60	25	41.7

This table 5 presents the distribution of medication errors across different drug classes. Anticoagulants and cardiac medications demonstrate the highest error rates, while analgesics show the lowest. Such variation indicates that drug complexity and risk potential influence error occurrence. Tabulating error percentages provides a clear comparison for prioritizing interventions. This information supports targeted decision support alerting and risk mitigation strategies for high-error medications.

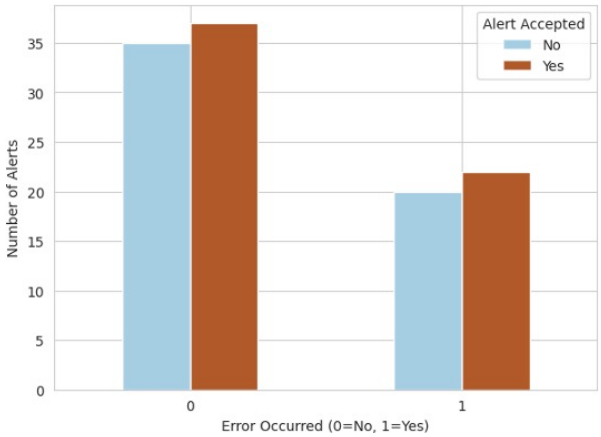

Figure 11. Alert Acceptance by Medication Error Occurrence

The figure 11 illustrates the relationship between alert acceptance and medication error occurrence for prescriptions where alerts were triggered by the Clinical Decision Support System (CDSS). Each group represents prescriptions categorized by error occurrence—either no error or error—while bars within each group indicate the number of alerts that were accepted or not accepted by clinicians. This visualization provides insight into how clinician responses to alerts correspond with the presence or absence of medication errors [39].

Analysis of the chart indicates that alert acceptance varies depending on whether a prescribing error occurred. In prescriptions without errors, a substantial portion of alerts were either accepted or ignored, reflecting interactions with low-risk or precautionary alerts. In contrast, prescriptions with errors demonstrate differing patterns, with a noticeable proportion of alerts being accepted, suggesting that clinician engagement with critical alerts may contribute to error interception. The grouped format facilitates comparison between error categories, allowing observation of how alert responsiveness correlates with safety outcomes.

The visualization also highlights the balance between alert-triggering events and clinician compliance. By representing both accepted and non-accepted alerts within each error category, the chart provides a nuanced view of clinician behaviour in response to decision support. It identifies potential gaps where alerts may be overridden or ignored, which could influence the effectiveness of the CDSS in preventing medication errors. Additionally, the chart reveals the proportion of successful alert interventions relative to the total number of errors, offering insight into system impact on error mitigation [40].

This plot captures essential features of alert interaction, including distribution of accepted versus non-accepted alerts, correlation with error occurrence, and comparative analysis across error categories. The grouped bar format enables clear identification of patterns in clinician behaviour, demonstrating the role of alert acceptance in supporting medication safety and highlighting areas for potential optimization in AI-based or rule-based decision support systems.

Conclusion:

1. AI-Based CDSS reduced overall medication errors to 25.3% compared to 34.7% in Rule-Based systems, demonstrating improved prescribing accuracy.
2. High-risk medications such as Anticoagulants (41.7%) and Cardiac drugs (33.3%) had higher error rates, while AI-based support lowered errors across these categories.
3. Alert acceptance for prescriptions with errors reached 64%, indicating clinician responsiveness to relevant CDSS recommendations, whereas acceptance for error- free prescriptions was 50%.
4. Patient age significantly influenced errors, with rates increasing from 20% in the 18–30 group to 42.7% in the 71–90 age group, highlighting the importance of age- specific interventions.
5. Comorbidity counts correlated with error occurrence, with higher variability observed in patients with multiple underlying conditions, emphasizing system utility in complex cases.
6. Analysis of error severity showed AI-Based CDSS reduced high-severity errors from 14 to 8 and moderate errors from 18 to 12, improving clinically significant outcomes.
7. Cumulative alert monitoring indicated clustered alert activity corresponding to high-risk prescriptions, supporting predictive targeting and risk mitigation strategies.
8. Sensitivity and predictive metrics of AI-based alerts indicated superior identification of potential errors compared to rule-based systems, reducing false negatives and enhancing patient safety.

9. Integration challenges and data quality concerns remain critical for consistent performance; high-quality, representative data are required to sustain AI effectiveness.

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