Improving Medication Error Detection with the Application of Transformer-based Models in Clinical Settings

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This paper utilizes data from peer-reviewed journals obtained through databases such as PubMed, EMBASE, and Medline. This paper is not intended for publication.

Abstract

The purpose of this systematized review investigated the application of transformer-based models in improving the detection of medication errors in clinical settings. The method of investigation for this review involved comprehensive database searches in PubMed, EMBASE, and Medline. Articles were screened according to the inclusion criteria of publication date in 2020 or later and the exclusion criteria of unrelated topics. Screening proceeded through titles/abstracts, then by full-text review to remove articles with the wrong outcome, reported no impact, occurred in the wrong setting (not a clinical setting), or was unavailable for full-text access. A total of 16 studies published between 2020 and 2024 met the inclusion criteria for this systematized review. The findings revealed that transformer-based models reduced the likelihood of medication errors. Computerized physician order entry systems, clinical decision support systems, ePrescribing, and artificial intelligence reduced drug, dosage, dispensing, administration, and patient-related medication errors. This systematized review highlights the effectiveness of transformer-based models in improving the detection of medication errors, demonstrating that transformer-based models reduce medication errors by enhancing detection processes in clinical settings.

Keywords: transformer-based models, computerized physician order entry systems, clinical decision support systems, ePrescribing, artificial intelligence, medication errors, clinical settings

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Introduction

Medication errors occur during the prescription, administration, and dispensing of medications. It is a significant challenge in clinical settings with frequent occurrences that impact patient safety. Medication errors are responsible for 5-41% of hospital admissions and 22% of readmissions (Tariq et al., 2024). Traditional methods of detecting medication errors are often inefficient. A medication error can result from a lack of training or knowledge, poor communication and documentation, increased workload, fatigued healthcare professionals, interruptions and distractions, and incorrect labeling (Tariq et al., 2024). Implementing advanced technologies, particularly transformer-based models, is essential to improve medication errors in clinical settings by accurately and effectively detecting these errors.

Transformer-based models, like computerized physician order entry (CPOE) systems, clinical decision support systems (CDSS), ePrescribing, and artificial intelligence (AI), enhance medication error detection by automating drug ordering processes. Transformer-based models improve efficiency by accelerating diagnoses, improving communication and documentation, and automating data analysis for personalized care (Devin et al., 2020). These models have demonstrated notable performance in recognizing, translating, and classifying clinical data to reduce the potential risk of medication error events.

The primary objective of this systematized review was to investigate the application of transformer-based models in improving the detection of medication errors in clinical notes, prescriptions, and patient records. Through a comprehensive analysis of current findings, this review addressed the question: Do transformer-based models enhance the accuracy and efficiency of medication error detection?

The method of investigation for this review included database searches in PubMed, EMBASE, and Medline to retrieve research articles and investigate the use and effectiveness of transformer-based models for medication error detection in clinical settings. This review synthesized current literature that reports improved medication error detection using transformer-based models. The principal result of this investigation highlighted the effectiveness of transformer-based models in medication error detection in various clinical settings. The results of this systematized review identified the impact of transformer-based models in medication error detection with decreased error rates after implementing transformer-based models. Finally, the principal conclusions drawn from this review suggested that transformer-based models, such as CPOE, CDSS, ePrescribing, and AI, presented a significant potential to reduce medication errors through enhanced accuracy and efficiency in clinical data analysis. The findings also outlined the challenges and limitations of applying transformer-based models in clinical settings.

Methods

Design

This review's method of investigation included database searches in PubMed, EMBASE, and Medline to retrieve research articles published between 2020 and 2024. The goal was to identify studies within the scope and eligibility of this systematized review. Studies that met the eligibility requirements for inclusion in this study were required to focus on the effect of transformer-based models on medication error and the error rate before and after implementation in clinical settings.

Tested Variables

The primary variables analyzed in this study included research articles that reported positive changes in medication error detection using transformer-based models. The assessed variables measured transformer-based models' accuracy, precision, and effectiveness in medication error detection. The tested variables also included the types of medication errors detected, such as drug, dosage, dispensing, administration, and patient-related medication errors. These variables were tested by the application of transformer-based models in clinical settings.

Control Conditions

The control condition within the literature involved comparing transformer-based models to traditional approaches, such as human and handwritten prescriptions and self-reported errors. The existing techniques and practices for medication prescription and error detection were investigated in terms of the frequency and quantity of errors and compared to the implementation and use of transformer-based models.

Procedures

The search strategy for this literature review was designed using a systematic approach that followed PRISMA guidelines. Search terms were created to capture all related papers that met the inclusion criteria in the searched databases (Page et al., 2021). The strategy was refined with Medical Subject Headings (MeSH) terms and keywords to identify all relevant studies that matched the nature and scope of the subject, ensuring a comprehensive review process.

Data Analysis

Publications that met the inclusion criteria were retrieved and screened by reviewing the titles and abstracts. Following the initial screening, the full text of each article was independently read and reviewed for the data analysis of this systematized review.

Results

Search Results

A total of 125 potential publications were identified via PubMed (n = 64), EMBASE (n = 18), and Medline (n = 43) in the database search (Fig. 1). After the removal of duplicate records, 122 titles and abstracts were screened to meet the inclusion criteria of publication date in 2020 or later, and the exclusion criteria of unrelated topics. After the initial screening, 51 publications were eligible for full-text review. The second screening process removed 35 articles that included the wrong outcome, reported no impact, occurred in the wrong setting (not a clinical setting), and was unavailable for full-text access (Fig. 1; Table 1).

Study Quality

This systematized review included 16 studies published between 2020 and 2024 (Fig. 1; Table 1). The publications included six literature reviews (n = 6), six direct observations (n = 6), three self-reports (n = 3), and one retrospective cohort study (n = 1) (Table 1). Most studies applied pre-post designs that implement a transformer-based model to examine the effectiveness of reducing medication errors or increasing medication error detection rates.

The extracted data from the included studies were measured and recorded using the following variables: author, year of publication, objective, method, and results (Table 1). All included studies focused on the effect of transformer-based models on medication error and the error rate before and after implementation in clinical settings.

Prescribing Systems

A notable pattern observed in the included studies is that half (n = 8) used a combination of two or more different prescribing systems for medication error detection, while the remaining half (n = 8) reported the use of only one prescribing system (Table 2).

The primary variables analyzed in this study included research articles that reported the use or investigation of the prescribing systems: CPOE, CDSS, ePrescribing, AI, or prescribing by humans to identify the tested variables: drug, dosage, dispensing, administration, and patient-related medication errors (Table 2).

Drug medication errors consist of inappropriate drugs, inappropriate combinations of drugs, inappropriate duplication, incomplete drug treatment, too many drugs prescribed, inappropriate drug formulation, inappropriate omission, expired products, and illegible writing (Table 2). Dosage medication errors included incorrect dosage, a dose of a single active ingredient that was too high, and the wrong dosage form (Table 2). Dispensing medication errors consisted of an unavailable prescribed drug, missing necessary information, incorrect rate, incorrect timing/duration, and timing instructions that were wrong/unclear/missing (Table 2). Administration medication errors consisted of the incorrect time given/taken, not taken as directed, and inaccurate preparation (Table 2). Patient-related medication errors included inappropriate drug monitoring, incorrect patient action, and medication adherence (Table 2).

Throughout the reviewed studies, transformer-based models consistently demonstrated reduced medication errors (Table 2). This trend suggests that transformer-based models significantly enhance error detection compared to traditional approaches.

Study Characteristics

Seven studies (n = 7) focused on all ages, four studies (n = 4) focused on pediatric patients 18 years or younger, two studies (n = 2) focused on adults 18 years or older, one study (n = 1) focused on elderly patients 60 years or older, and two studies (n = 2) did not have or did not report a population age (Table 3).

All included studies (n = 16) took place in clinical settings (Table 3). The identified studies from the initial database search performed in non-clinical settings, such as schools, workplaces, community centers, and correctional facilities, were excluded from this systematized review (Fig. 1). However, the geographical location of the included studies varied by country, where six included studies (n = 6) involved two or more countries (Table 3).

Medication errors were reduced across the included studies, with decreased drug, dosage, dispensing, administration, and patient-related errors (Table 2). This trend highlights the substantial potential of CPOE, CDSS, ePrescribing, and AI to reduce medication errors by improving data analysis in acute and primary care settings. Studies reported patterns of improvements in dispensing processes, data accessibility, prescribing error rates, and administration error rates. Additionally, the results demonstrated effectiveness in minimizing dosage and dispensing inaccuracies. These findings suggest that transformer-based models contribute to a more proactive approach to medication error prevention for enhanced patient outcomes.

Discussion

Numerous studies analyzed the effectiveness of transformer-based models in improving medication error detection. This review identified 16 studies within the scope of this review. These 16 studies emphasize the rates of medication error and error detection with traditional approaches compared to transformer-based models. Medication errors occur when ordering, prescribing, dispensing, administering, and monitoring; notably, approximately 50% of all medication errors occur when a medication is prescribed or ordered (Tariq et al., 2024). The primary objective of this review was to investigate the application of transformer-based models in improving medication error detection in clinical settings. All studies reported a positive change in medication error and detection using transformer-based models. The results of this review identified the impact of transformer-based models on decreasing medication error rates.

Medication Error

The presence of transformer-based models reduces the likelihood of lost, misplaced, or missing medication orders and eliminates illegible handwritten orders (Liang et al., 2021). Several studies have recognized the cause of medication errors. Yoon and Sohng (2021) examined 805 self-reported events to identify the cause of near-misses and adverse drug events. The authors found that 34.9% resulted from the wrong drug, 18.6% from the wrong dose, 17.5% from the wrong patient, route, time, or place, and 28.5% from omission or duplication (Yoon & Sohng, 2021). Manias et al. (2021) reported an odds ratio (OR) of 0.69 (confidence interval (CI): 0.618-0.771) for medication errors caused by doctors, an OR of 0.327 (CI: 0.267-0.401) caused by pharmacists, and an OR of 0.647 (CI: 0.472-0.870) caused by patients or families. These studies suggest that traditional approaches for medication error detection exhibit significant shortcomings.

Aside from common causes for medication errors, a recent study reported that patient age and clinician education level also affect medication error rates. Patient age, associated with rates of medication error, resulted in an OR of 0.949 (CI: 0.940-0.957) in univariate and an OR of 0.946 (CI: 0.932–0.960) in multivariate (Mo & Wu, 2024). This study indicated that patient age contributes to increased medication error rates due to the possibility of confusion, lack of understanding or incomprehension, the presence or lack of presence of a guardian or caretaker, or misread or unread instructions (Mo & Wu, 2024). In addition, specialized nursing roles correlate to reduced rates of medication error with an OR of 0.229 (CI: 0.176–0.300) in univariate and an OR of 0.291 (CI: 0.189–0.447) in multivariate (Mo & Wu, 2024). These findings suggest that specialized nursing roles provide more diminutive nurse-to-patient ratios, which permits more time dedicated to assigned patients and their medications. It also allows optimal time for effective counseling, bedside conversation, documentation, reports, and clinical handovers by eliminating the need to rush and removing interruptions.

CPOE and CDSS

Numerous studies examined the rates of medication error pre-CPOE and post-CPOE implementation. One study reported positive impacts of CPOE on medication supply, allowing for improved dispensing processes and data accessibility for enhanced clinical interventions (Amir & Khan, 2022). Manias et al. (2020) observed reduced prescribing error rates in 14 out of 26 studies and reduced administration error rates in 4 out of 11 studies. This finding is consistent with that of Devin et al. (2020), who found a reduction in prescribing error rates in 34 of 35 studies. Similarly, Hajesmaeel et al. (2021) identified a 54.5% decrease in medication error rates.

Six of the included studies examined both CPOE and CDSS, whereas Zwietering et al. (2024) performed a direct observational study in hospitalized elderly patients to explore the effect of CDSS intervention without integrating CPOE. The study showed that CDSS resolved 7,907 out of 8,703, or 97.7% of alerts (Zwietering et al., 2024).

Three recent studies explored medication errors in the pediatric population. Liang et al. (2023) analyzed the impact of CPOE systems in a pediatric hospital. The authors found 133 (47.0%) medication errors per every 10,000 prescription orders pre-CPOE and 109 (39.1%) medication errors per every 10,000 prescription orders post-CPOE, resulting in a 7.9% reduction (Liang et al., 2023). These results align with the findings of Satir et al. (2023), who similarly analyzed the impact of CPOE systems in a pediatric hospital and concluded that CPOE reduced medication errors from 18 (CI: 17–20) to 11 (CI: 9–12) errors per every 100 prescription orders.

The third study focusing on the pediatric population, in both inpatient and outpatient settings, examined the effects of CPOE systems integrated with CDSS on medication dose errors, suggesting CPOE-CDSS have the potential to reduce pediatric dose errors (Ruutiainen et al., 2024).

ePrescribing and AI

A study on the effects of ePrescribing in acute and primary care settings concluded that ePrescribing especially contributes to reducing medication errors (Guilcher et al., 2023). Furthermore, general trends are apparent in studies examining AI's impact on medication error detection. Damiani et al. (2023) reported that 71% of their reviewed studies reported decreased medication errors. Comparably, Paris et al. (2024) reported that AI reduced 33% of near-miss events. These studies' results agree with the parallel findings by Manias et al. (2021), which indicated that adding electronic prescribing and dispensing systems decreases medication errors.

Findings suggest that transformer-based models improve the detection of medication errors by enhancing accuracy and efficiency across drug, dosage, dispensing, administration, and patient-related medication errors. Integrating CPOE, CDSS, ePrescribing, and AI improved medication error detection and prevention.

Limitations

This study includes a few limitations. First, the variability in the methods and designs of the included studies may impact the generalizability of the results. Second, the varying definitions and measurements of medication errors across the studies can also affect the collective findings. Third, the high costs for transformer-based systems, training, and technical resources decrease the likelihood of implementation in clinical settings. Lastly, this review only included studies published within the last four years.

Future Research

Further research is needed to evaluate the financial benefit of transformer-based models over time and whether the profit outweighs the implementation expenses. Additionally, current literature suggests the need for research on the direct correlation between medication error detection using transformer-based models and its effectiveness in improving patient safety.

Conclusion

The principal result of this investigation highlighted the effectiveness of transformer-based models in medication error detection in various clinical settings. Concerning the research question addressed in this review, an analysis of the 16 included publications concluded that transformer-based models improve medication error detection rates by implementing CPOE, CDSS, ePrescribing, and AI. Finally, the principal conclusions drawn from this review suggest that implementing transformer-based models in clinical settings will reduce medication errors by enhancing detection processes.

References

Amir, M., & Khan, A. (2022). Implementing computerized physician order entry in a public tertiary care hospital. *The Journal of Medicine Access, 6*, 27550834221119689. 10.1177/27550834221119689

Damiani, G., Altamura, G., Zedda, M., Nurchis, M. C., Aulino, G., Heidar Alizadeh, A., Cazzato, F., Della Morte, G., Caputo, M., Grassi, S., Oliva, A., & D 3 2 group. (2023). Potentiality of algorithms and artificial intelligence adoption to improve medication management in primary care: a systematic review. *BMJ Open, 13*(3), e065301–065301. 10.1136/bmjopen-2022-065301

Devin, J., Cleary, B. J., & Cullinan, S. (2020). The impact of health information technology on prescribing errors in hospitals: a systematic review and behaviour change technique analysis. *Systematic Reviews, 9*(1), 275–7. 10.1186/s13643-020-01510-7

Guilcher, S. J. T., Cimino, S. R., Tadrous, M., McCarthy, L. M., Riad, J., Tricco, A. C., Hagens, S., Lien, J., Tharmalingam, S., & Gomes, T. (2023). Experiences and Outcomes of Using e-Prescribing for Opioids: Rapid Scoping Review. *Journal of Medical Internet Research, 25*, e49173. 10.2196/49173

Hajesmaeel Gohari, S., Bahaadinbeigy, K., Tajoddini, S., & R Niakan Kalhori, S. (2021). Effect of Computerized Physician Order Entry and Clinical Decision Support System on Adverse Drug Events Prevention in the Emergency Department: A Systematic Review. *The Journal of Pharmacy Technology: jPT : Official Publication of the Association of Pharmacy Technicians, 37*(1), 53–61. 10.1177/8755122520958160

Liang, M. Q., Boudjellab, A., Kwon, H., Jouvet, P., Lebel, D., Thibault, M., & Motulsky, A. (2021). Implementation of a Computerized Provider Order Entry System in a Pediatric

Hospital in Canada. *Studies in Health Technology and Informatics, 281*, 590–594. 10.3233/SHTI210239

Liang, M. Q., Thibault, M., Jouvet, P., Lebel, D., Schuster, T., Moreault, M., & Motulsky, A. (2023). Improving medication safety in a paediatric hospital: a mixed-methods evaluation of a newly implemented computerised provider order entry system. *BMJ Health & Care Informatics, 30*(1), e100622. 10.1136/bmjhci–100622. 10.1136/bmjhci-2022-100622

Manias, E., Kusljic, S., & Wu, A. (2020). Interventions to reduce medication errors in adult medical and surgical settings: a systematic review. *Therapeutic Advances in Drug Safety, 11*, 2042098620968309. 10.1177/2042098620968309

Manias, E., Street, M., Lowe, G., Low, J. K., Gray, K., & Botti, M. (2021). Associations of person-related, environment-related and communication-related factors on medication errors in public and private hospitals: a retrospective clinical audit. *BMC Health Services Research, 21*(1), 1025–8. 10.1186/s12913-021-07033-8

Mo, L., & Wu, Z. (2024). Investigating risk factors for medication errors during perioperative care: A retrospective cohort study. *Medicine, 103*(22), e38429. 10.1097/MD.0000000000038429

Pais, C., Liu, J., Voigt, R., Gupta, V., Wade, E., & Bayati, M. (2024). Large language models for preventing medication direction errors in online pharmacies. *Nature Medicine, 30*(6), 1574–1582. 10.1038/s41591-024-02933-8

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, n71. https://doi.org/10.1136/bmj.n71

Ruutiainen, H., Holmstrom, A., Kunnola, E., & Kuitunen, S. (2024). Use of Computerized Physician Order Entry with Clinical Decision Support to Prevent Dose Errors in Pediatric Medication Orders: A Systematic Review. *Paediatric Drugs, 26*(2), 127–143. 10.1007/s40272-023-00614-6

Satir, A. N., Pfiffner, M., Meier, C. R., & Caduff Good, A. (2023). Prescribing errors in children: what is the impact of a computerized physician order entry? *European Journal of Pediatrics, 182*(6), 2567–2575. 10.1007/s00431-023-04894-5

Tariq, R. A., Vashisht, R., Sinha, A., & Scherbak, Y. (2024). Medication Dispensing Errors and Prevention. *StatPearls* (). StatPearls Publishing LLC.

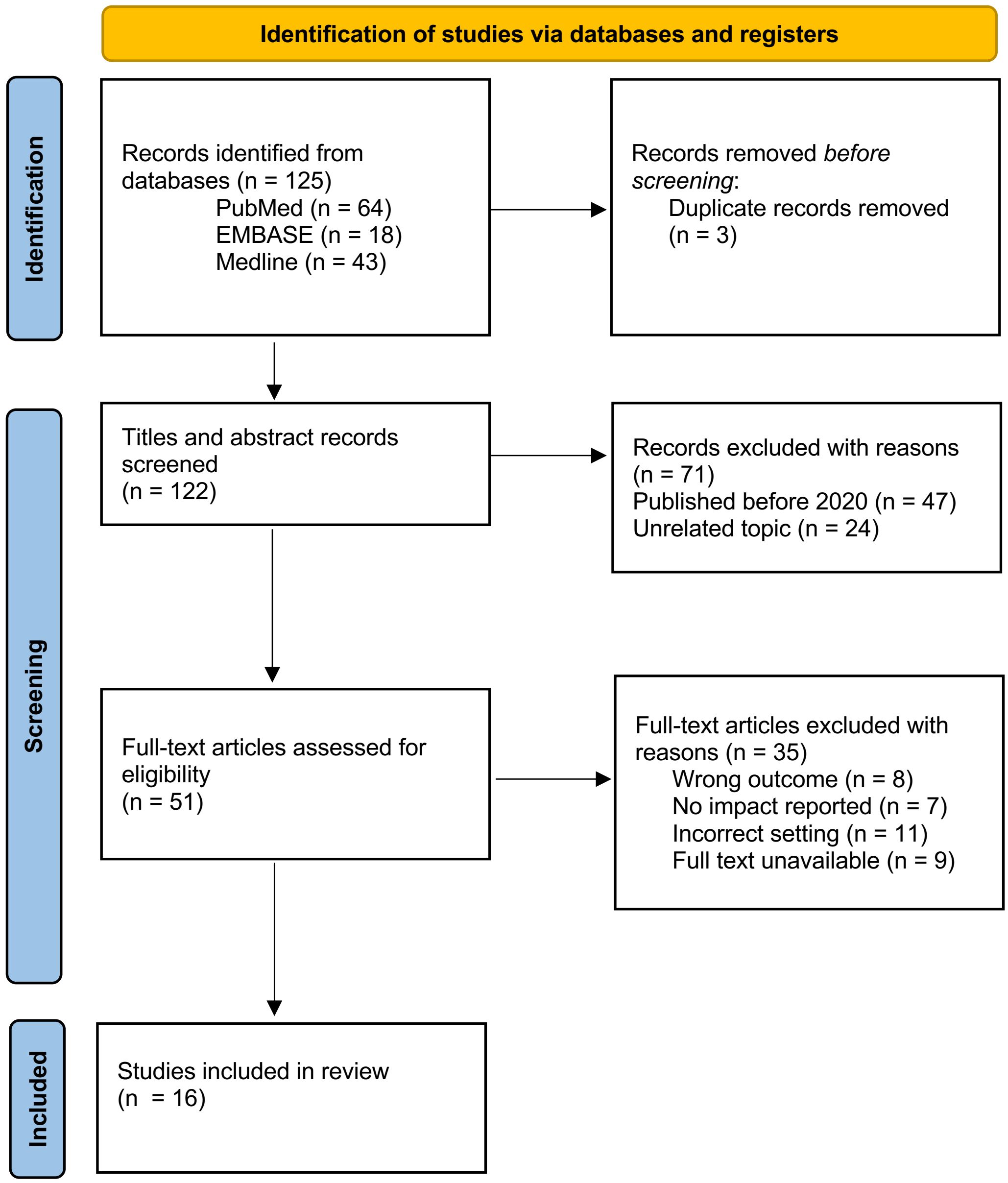
Yoon, S., & Sohng, K. (2021). Factors causing medication errors in an electronic reporting system. *Nursing Open, 8*(6), 3251–3260. 10.1002/nop2.1038

Zwietering, N. A., Linkens, A., Kurstjens, D., van der Kuy, P., van Nie-Visser, N., van de Loo, B., Hurkens, K., & Spaetgens, B. (2024). Clinical decision support system supported interventions in hospitalized older patients: a matter of natural course and adequate timing. *BMC Geriatrics, 24*(1), 256–7. 10.1186/s12877-024-04823-7

Appendix

Figure 1

PRISMA 2020 Flow Diagram for Searches in Databases and Registers



Note. This figure illustrates the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram of different screening processes to select eligible publications for inclusion in this systematized literature review.

Table 1

Overview of Studies Included in the Systematized Literature Review (n = 16)

Authors (year)	Objective	Method	Results
Manias et al. (2020)	To compare the effectiveness of different interventions for reducing medication errors in acute settings.	Literature review	- Prescribing error rates were reduced in 14 out of 26 studies. Administration error rates were reduced in 4 out of 11 studies.
Devin et al. (2020)	To assess the health information technology that reduces prescribing errors in hospitals and identify behavior change techniques.	Literature review	- Prescribing error rates were reduced in 34 out of 35 studies.
Hajesmaeel et al. (2021)	To assess the effectiveness of CPOE and CDSS in reducing adverse drug events in the emergency department.	Literature review	- CPOE and CDSS decrease medication error rates in 54.5% of articles.
Liang et al. (2021)	To assess the impact of CPOE on medication errors in a pediatric unit.	Direct observation	- CPOE reduced missing medication orders and eliminated illegible orders.
Manias et al. (2021)	To assess person, environment, and communication-related factors on medication errors.	Direct observation	- 11540 medication errors were reported. - OR 0.690, CI: 0.618-0.771 medication errors caused by doctors. - OR 0.327, CI: 0.267-0.401 caused by pharmacists. - OR 0.641, CI: 0.472-0.870 cause by patients or families. - Incidents were due to reports of insufficient counseling of patients, movement across transitions of care, presence of interruptions, presence of covering personnel, misread or unread orders, informal beside conversations, and problems with clinical handovers. - The presence of electronic prescribing and dispensing systems reported reduced medication errors in comparison to the absence of these systems.
Yoon and Sohng (2021)	To analyze the effectiveness of a hospital's electronic reporting system on medication error data.	Direct observation	- From the 805 self-reported near misses and adverse drug events, 34.9% were wrong drug, 18.6% were wrong dose, 17.5% were wrong patient/route/time/place, and 28.9% were omission/duplication.

Amir and Khan (2022)	To assess the barriers and process of implementing CPOE systems in a hospital.	Self-report	- CPOE reduced medication floor stock and allowed pharmacy to dispense medication patient-wise. - CPOE improved clinical pharmacy services by providing access to all relevant data to conduct clinical intervention, whereas the manual process prevented pharmacist from providing pharmaceutical care services due to lack of time.
Liang et al. (2023)	To analyze the impact of CPOE system on medication safety in a pediatric hospital and suggest potential error prevention strategies.	Direct observation	- 133 medication errors/47.0% per 10000 orders were reported pre-CPOE and 109/39.1% per 10000 orders were reported post-CPOE. - Most medication errors occurred during the nurse administration step.
Damiani et al. (2023)	To investigate the effect of AI and/or algorithms on drug management in primary care settings, and evaluate the most frequent type of reported medication error.	Literature review	- 71% of studies reported reduced medication errors with the use of AI.
Satir et al. (2023)	To investigate the impact of CPOE on prescribing errors in children.	Direct observation	- Medication errors were reduced from 18 errors per 100 prescriptions (CI: 17-20) to 11 errors per 100 prescriptions (CI: 9-12) with CPOE.
Guilcher et al. (2023)	To examine the effects of e-prescribing in clinical settings.	Literature review	- ePrescribing contributes to reduced medication errors.
Tariq et al. (2024)	To identify types of medication errors and their causes, and implement strategies to minimize medication error.	Self-report	- Reported medication errors occur when ordering, prescribing, transcribing, dispensing, administering, monitoring. Approximately 50% of all medication errors occur when a medication is prescribed or ordered.
Ruutiainen et al. (2024)	To examine the effects of CPOE systems with CDS function in medication dose errors in pediatric medications.	Literature review	- Reported CPOE-CDS systems may reduce pediatric dose errors.
Zwietering et al. (2024)	To analyze the effectiveness of CDSS in hospitalized elderly patients.	Direct observation	- 7907 of 8703 alerts (97.7%) were resolved due to CDSS intervention.
Mo and Wu (2024)	To examine the risk factors of medication error during perioperative care.	Retrospective cohort study	- Increased education and advanced titles correlate inversely with the risk of medication error. - Patient age is associated with rates of medication error; OR 0.949, CI: 0.940–0.957 in univariate; OR 0.946, CI: 0.932–0.960 in multivariate. - Specialized nursing roles are associated with reduced rates of medication error; OR 0.229, CI: 0.176–0.300 in univariate; OR 0.291, CI: 0.189–0.447 in multivariate.
Paris et al. (2024)	To assess the effectiveness of LLMs in text interpretation and generation to reduce medication errors.	Self-report	- 33% near-miss events reduced after the implementation of MEDIC, an AI system online pharmacy.

Note. This table identifies the included studies, their objectives, methods, and key findings/results.

* Abbreviations: CPOE = Computerized Provider Order Entry; CDS/CDSSS = Clinical Decision Support System; OR = Odds Ratio; CI = Confidence Interval; AI = Artificial Intelligence; LLM = Large Language Model

Table 2

Characteristics of identified medication errors by prescribing system

Authors (year)	Type of prescribing system					Type of medication error				
	CPOE	CDSS	ePrescribing	AI	Human	Drug[a]	Dosage[b]	Dispensing[c]	Administration[d]	Patient-related[e]
Manias et al. (2020)	x	x			x	x	x	x	x	x
Devin et al. (2020)	x	x	x		x	x	x	x	x	x
Hajesmaeel et al. (2021)	x	x				x	x	x	x	
Liang et al. (2021)	x				x	x	x	x	x	x
Manias et al. (2021)					x	x	x	x	x	x
Yoon and Sohng (2021)					x	x	x	x	x	x
Amir and Khan (2022)	x							x	x	
Liang et al. (2023)	x	x			x	x	x	x	x	x
Damiani et al. (2023)				x		x	x			x
Satir et al. (2023)	x				x	x	x	x	x	x
Guilcher et al. (2023)			x			x	x	x		x
Tariq et al. (2024)	x	x			x	x	x	x	x	x
Ruutiainen et al. (2024)	x	x				x	x			
Zwietering et al. (2024)		x					x			x
Mo and Wu (2024)					x	x	x	x	x	x
Paris et al. (2024)				x		x	x	x	x	

Note. This table demonstrates the characteristics of medication error by detection method type.

* Abbreviations: CPOE = Computerized Provider Order Entry; CDSS = Clinical Decision Support System

[a] Drug: inappropriate drug, inappropriate combination of drugs, inappropriate duplication, incomplete drug treatment, too many drugs prescribed, inappropriate drug formulation, inappropriate omission, expired product, and illegible writing.

[b] Dosage: incorrect dose, dose of a single active ingredient too high, and/or wrong dosage form.

[c] Dispensing: unavailable prescribed drug, missing necessary information, incorrect rate, incorrect timing/duration, and timing instructions wrong/unclear/missing.

[d] Administration: given at the incorrect time, taken at the incorrect time, not taken as directed, and incorrect preparation.

[e] Patient-related: inappropriate drug monitoring, incorrect patient action, and medication adherence.

Table 3

Characteristics and Demographics of Included Studies (n = 16)

Authors (year)	Clinical setting	Sample Size	Age	Location
Manias et al. (2020)	Hospital - adult medical and surgical settings	34 studies	≥18	Various
Devin et al. (2020)	Hospital - various units	35 studies	All	Various
Hajesmaeel et al. (2021)	Emergency department	11 studies	All	Various
Liang et al. (2021)	Hospital - pediatric medicine unit	60 beds, 375 manuscript orders, 521 electronic orders	≤18	Canada
Manias et al. (2021)	Private and public hospitals - various units	1500 beds at 7 public hospitals, 1550 beds at 9 private hospitals, 11,540 medication errors reported	All	Australia
Yoon and Sohng (2021)	Hospital - various units	850 beds, 805 near misses and adverse events	All	South Korea
Amir and Khan (2022)	Hospital - various units	1770 beds	All	Pakistan
Liang et al. (2023)	Hospital - pediatric medicine unit	60 beds, 28,302 orders pre-CPOE, 27,887 orders post-CPOE	≤18	Canada
Damiani et al. (2023)	Primary care settings	14 studies	All	Various
Satir et al. (2023)	Hospital - pediatric wards	1000 patients	≤18	Switzerland
Guilcher et al. (2023)	Acute care and primary care settings	33 studies	All	Various
Tariq et al. (2024)	NR	NR	NR	United States
Ruutiainen et al. (2024)	Pediatric inpatient and outpatient settings	17 studies	≤18	Various
Zwietering et al. (2024)	Hospital - geriatric unit	3574 patients	≥60	The Netherlands
Mo and Wu (2024)	Hospital - various units	1723 patients	≥18	China
Paris et al. (2024)	Amazon Pharmacy	1200 prescriptions	NR	United States

* Abbreviations: NR = Not Reported