REVIEW ARTICLE

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Artificial Intelligence in Managing and Reducing Medication Errors: A Systematic Review

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Abstract

Background: In studies examining adverse events in hospitals, medication errors were identified as the primary or contributing factor in nearly one out of every five incidents. Research has shown that artificial intelligence and machine learning algorithms can assist doctors in making more accurate diagnoses and outperform human practitioners in predicting certain medical outcomes. Reducing medication errors (MEs) is most crucial in three areas: electronic prescriptions, medication error surveillance, and barcode medication administration systems. This Systematic Review examines the role and applications of artificial intelligence in the management and reduction of medication errors.
Methods: Searches were conducted for Randomized Clinical Trials in English on PubMed, Web of Science, Scopus, Science Direct and IEEE Xplore, from inception to 2024/9/18. Also, the Google Scholar search engine has been reviewed. risk of bias and quality were assessed with the Cochrane risk-of-bias (ROB) 2.0 tool. The review followed PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines (Fig.1). The Protocol has been registered in PROSPERO by code: CRD42024590942
Results: The search strategy identified a total of 45824 articles, of which 19 articles were included in the review. In these studies, five areas were included: education and learning, quality improvement, medication error prediction, medication error detection, and medication error management.
Conclusion: This Systematic review shows that AI significantly reduces medication errors by improving prediction, detection, and management. It enhances safety and efficiency but still faces challenges in privacy, ethics, and system integration.

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Introduction

Medication errors are particularly significant due to the increasing global volume of medication use. They are the most common medical error in healthcare settings, with much of the related literature focusing on hospitals. (1, 2) In some countries, it is estimated that approximately 6–7% of hospital admissions are related to medication, with more than two-thirds of these cases being avoidable. (3-5) In studies of adverse events in hospitals, medication errors were identified as a primary or contributing factor in nearly one in five cases. (6-9) This has resulted in increased centralization on epidemiology and the prevention of medication errors in hospital settings worldwide, activating numerous studies. (10-18) This partnership has not yielded clear or consistent findings about medication errors. Conversely, there seems to be a variety of terms used to describe the clinical scope of medication errors and classify outcomes: error, failure, near miss, rule violation, deviation, preventable adverse drug event (ADE), and potential ADE. (18-22) Additionally, it has been proposed that this inconsistency has led to significant variations in the reported incidence of medication errors.(23-25) There is no agreement on what constitutes a medication error. (26) Medication errors can occur due to inadequate medication systems, human factors like fatigue, or poor working conditions such as excessive workloads and understaffing.(27) Estimating the incidence of medication errors is challenging due to the various definitions and classification systems utilized.(28) Negative outcomes include adverse drug reactions, drug-drug interactions, insufficient efficacy, poor patient adherence, and diminished quality of life and patient experience. These issues can lead to significant health and economic consequences. (29) Improving medication security and reducing medication errors requires a systems approach. Strategies include using clinical pharmacists, AI, computer technology, and educational programs, often as part of multifaceted interventions. (30) Electronic prescribing systems, monitoring of medication errors, and barcoded medication administration systems are the key areas to reduce medication errors. (31) Modern computer systems and applications in the healthcare field are now seen as a key strategy to reduce medical errors, minimize adverse events, facilitate quicker responses after such events, and provide valuable feedback regarding them. (32) Artificial intelligence is one of the fields of computer science, the purpose of which is to simulate the processes of human intelligence, learning capacity and knowledge storage by machines, especially computer systems, which today affect almost every aspect of the human condition (33-35) Machine learning allows computers to handle large data with complex relationships, while traditional statistical methods often struggle with large data. (36) Utilizing AI in healthcare can lead to both challenges and opportunities for profit. (37, 38) Using AI in healthcare offers several advantages, such as better management of patient choices and outcomes, fewer referrals, reduced costs, and time savings. However, there are also challenges, including the need for early adoption, acceptable performance within the healthcare system, and a lack of consideration for the user's perspective. (38) Investments in the expansion of artificial intelligence tools are increasing, and improvements in this field have led to the convergence of healthcare and technology. (38, 39) IT-based interventions, such as computerized provider order entry (CPOE) with clinical decision support (CDS) and telemedicine interventions, have been widely promoted as the most effective strategies for improving medication safety across all clinical settings. (40) Computerized physician order entry (CPOE) eliminates handwritten orders, thereby reducing errors related to medication prescribing. (41, 42) Numerous studies have shown that artificial intelligence and machine learning algorithms can assist doctors in making more accurate diagnoses. In some cases, these technologies outperform human practitioners when it comes to diagnosing specific diseases or predicting certain medical outcomes, such as mortality rates or the length of hospital stay. (43-47) The purpose of this article is to examine the role and applications of artificial intelligence in the management and reduction of medication errors, examine artificial intelligence algorithms in this field, identify popular algorithms and examine smart systems in the field of medication errors.

Materials and methods

Study design

We systematically searched five databases, namely PubMed, Web of Science, Scopus, Science Direct, and IEEE Xplore, to find relevant articles based on the keywords used in our search strategy from inception to 2024/9/18. Also, the Google Scholar search engine has been reviewed. Screening was conducted in two stages involving two independent researchers. In the first stage, titles and abstracts were reviewed, followed by a full-text screening process in the second stage. The data extraction and summarization of the included studies was carried out by two independent researchers. Any remaining discrepancies were resolved by a third researcher. The PICO framework used in this study is: P: Patients, I: Artificial intelligence, C: Medication errors decrease factor, O: medication errors. The reporting methodology in this study followed the PRISMA 2020 checklist (Preferred Reporting Items for Systematic

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Reviews and Meta-Analysis). The Protocol has been registered in PROSPERO by code: CRD42024590942.

Search strategy

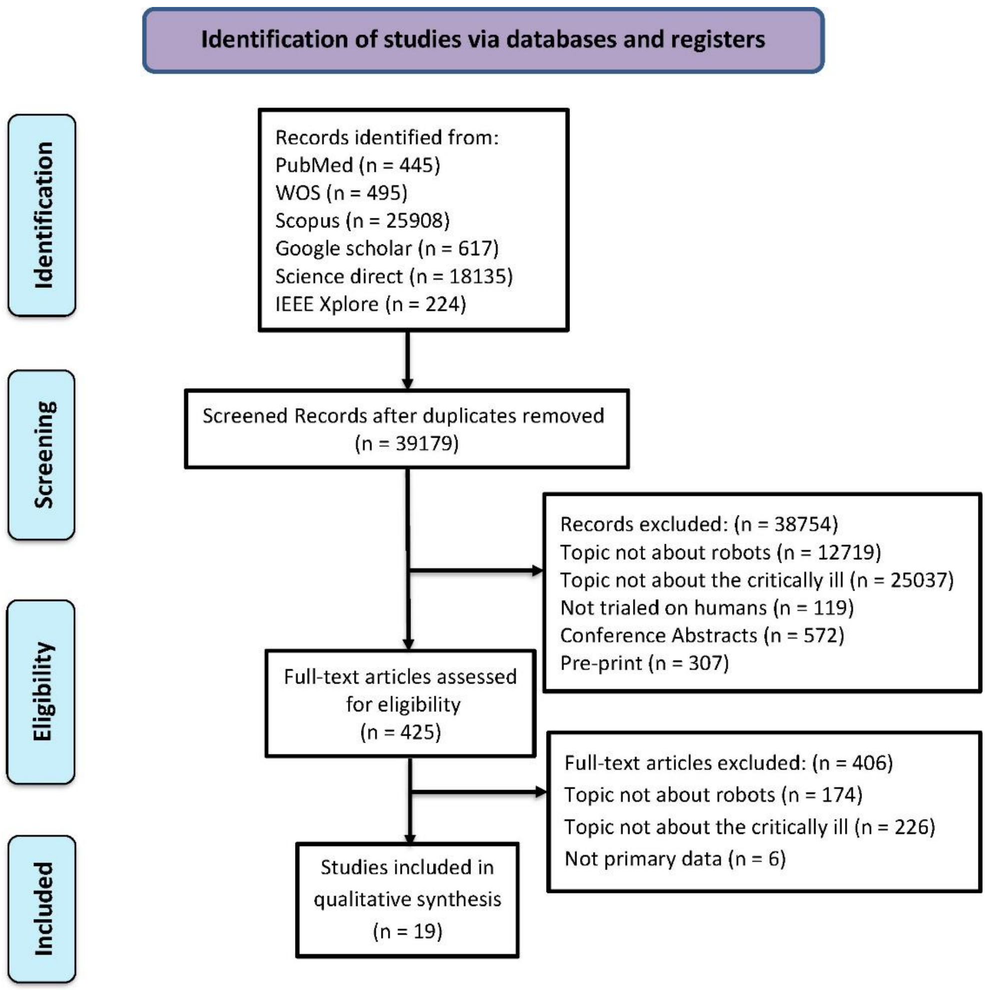
The search strategy concentrated on two main concepts: Artificial intelligence and Medication error. We utilized appropriate free-text words and Medical Subject Headings (MeSH) terms to identify relevant studies for each key concept. Google Scholar has very limited advanced search options, so the keywords were modified and the most relevant results were assessed. For the Google Scholar search, the following terms were utilized: "Artificial Intelligence" OR "Machine Learning" AND "Medication error" OR "Adverse event" OR "Drug Use Error". The references of the articles included in our study were reviewed and adapted with our method and flowchart. A detailed search strategy for Databases is provided in S1 Table.

Search strategy included:

1. "Artificial intelligence" OR "Machine learning" OR "Deep Learning" OR "New technologies" OR "Computer reasoning" OR "Computational intelligence" OR "Computer vision system" OR "Knowledge acquisition" OR "Knowledge representation" [All fields]

2. "Medication error" OR "Adverse event" OR "Drug Use Error" [All fields]

3. [A] AND [B].



Selection criteria

We included all English interventional studies that investigated the effect of artificial intelligence on managing medication errors and reducing them. The exclusion criteria were as follows:

(1) Review articles, Editorials, or other studies that do not include original data.

(2) Ongoing studies.

(3) This research does not consider studies that are unrelated to its aims, settings, and design.

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(4) Abstracts, conference abstracts, errata, or other studies lacking full texts, and studies whose full text was not in English.

Data extraction

The authors' names, publication dates, study types, sample sizes, control groups, instruments, and study results were recorded independently by two authors on an information sheet and any remaining discrepancies were resolved by a third researcher. In this systematic review (45824) documents were identified. After a primary review of retrieved articles, (6645) duplicates were removed, and the title and abstract of the remaining articles were reviewed. (38754) articles were excluded after applying the selection criteria. (425) full-text articles were assessed for eligibility, with (406) of them being excluded due to irrelevance, being reviews, letters to the editor, not being original articles, Topics not about robots, Topics not about the critically ill or not primary data. Ultimately, (19) articles met the inclusion criteria and were included in the final review (Fig. 1)

Risk of bias assessment

The quality of all studies was assessed by two raters, while three other raters divided the studies. The between-rater agreement factor was calculated and Key disagreements were addressed through discussions aimed at defining the final selection of included studies. also we use Cochrane Risk of Bias (ROB) 2.0 Tool (48) for Risk of bias / Quality assessment.

Reporting and ethical consideration

The results of the systematic review were reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (49) Being designed as a systematic review extracting data from published articles, an ethical review for this study might be exempt. However, information about the ethical approval of the selected articles was reported as part of the quality assessment.

Results

In this systematic review (45824) documents were identified. After a primary review of retrieved articles, (6645) duplicates were removed, and the title and abstract of the remaining articles were reviewed. (38754) articles were excluded after applying the selection criteria. (425) full-text articles were assessed for eligibility, with (406) of them being excluded due to irrelevance, being reviews, letters to the editor, not being original articles, Topics not about robots, Topics not about the critically ill, Not trialed on humans, Conference Abstracts, Pre-print or Not primary data. Ultimately, (19) articles met the inclusion criteria and in the final review, five areas were included: education and learning, quality improvement, medication error prediction, medication error detection, and medication error management. The Cochrane Risk of Bias (ROB) tool identifies a low risk of bias in performance, randomization, attrition, and outcome assessment in the clinical trial review, which enhances confidence in the reliability of the results. Most of the studies received a favorable score in selection, entry and exit criteria, comparison, data analysis, and clarity of results.

automatic and intelligent monitoring system

- The use of intelligent pharmaceutical systems in the direction of reduction Medication errors of the elderly at home, according to studies, the automatic and intelligent monitoring system is able to monitor the person's condition at all times Controls and informs the level of risk so that it sends messages to designated people when necessary. Autonomous and intelligent system(Aims) is based on artificial intelligence and the proposed model named AMED is installed on the mobile phone and its reminder is through voice or video message that checks the images with the approval of the person and sends the image and gives feedback based on it. (50)
- The evaluation and implementation of the Medley system demonstrated that approximately 18,500 alerts and 4,000 programming changes occurred during the study period. The use of this system facilitated faster access to medication information and enhanced safety alert .The integration of this medication safety system, with its direct support for clinical practice, attracted significant attention from physicians and nurses. The alerts generated by the system frequently resulted in adjustments to medication programming, and its implementation effectively improved the quality of care and patient safety to an optimal level.(51)
- This study proposes a system based on tablet recognition using printed characters, assuming that the most important information lies in the printed characters on the tablet. This system can identify tablets that are not part of the training data set and has higher accuracy than the basic system that uses CNNs.(52)
- The clinical decision support system, which uses a probabilistic machine learning approach based on statistical post-hoc data to identify medication errors, had a low alert burden, with 89% of these alerts being accurate. During the study, 135 medication orders were modified. The most frequent alerts that caused a change in physician behavior were related to medication dosage. Overall, the system had a low alert burden and a low false positive rate. (53)
- With the introduction of DST, coding time was reduced by 10%. Integrating DST into the damage monitoring workflow results in timely reporting and also increases accuracy in the three fields of damage intent, external cause, and damage agent. (54)

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Table. AI in medication error: Study Summary (Randomized Clinical Trial)

code	Article	Country	Artificial Intelligence Algorithm	Outcome
1	Maphosa 2024 (55)	Zimbabwe	RF	The developed RF-based model can identify and correct prescription and prescribing errors, enhance the accuracy of medications, and improve patient safety.
2	NGUYEN 2024 (56)	Japan	GCN (Graph Convolutional Network) Contrastive learning	The results suggest that the proposed method may reduce medication errors and enhance patient safety.
3	Natsiavas 2024 (57)	Greece	PrescIt platform	The PrescIT platform has been successfully deployed and piloted in real-world settings to evaluate its effectiveness in supporting safer medication prescriptions.
4	Feng 2024 (58)	China	DKADE	Our results indicate that utilizing a knowledge graph leads to improved F1 scores and recall. Both experimental and external validation results demonstrate that DKADE can effectively identify and extract adverse drug events (ADEs) and related medications from complex Chinese semantic texts. By learning ADE-related knowledge from a large volume of Chinese descriptions of ADEs, DKADE can enhance adverse event surveillance and contribute to drug safety studies.
5	Pais 2023 (59)	India	KNN	The K-Nearest Neighbor (KNN) algorithm demonstrated the best performance compared to the other algorithms. The KNN algorithm can be utilized to develop a model that assists doctors and nurses in prescribing medication at the right time and in the appropriate dosage, ultimately saving patients' lives. Additionally, the model can be enhanced by testing it with deep learning algorithms, with performance measurements to follow.
6	Heo 2022 (52)	United States of America	RNN,ResNet,YOLO	We suggest that this system can minimize patients' misuse of medications and allow medical staff to concentrate on higher-level tasks by streamlining time-consuming lower-level tasks, such as pill identification.
7	Catchpoole 2022 (54)	Australia	ED systems based on emergency department, DST	The integration of the DST into the injury surveillance workflow provides advantages by facilitating timely reporting and serving as a DST in the manual coding process.
8	Naeem 2022 (60)	Italy	Deep Learning based classifierI	This integration of three different tools to monitor the medication process reduces the likelihood of medication errors and enhances accurate detection.

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9	McMaster 2021 (61)	Australia	ADRs	Our study showcases the potential of natural language processing (NLP) models for automating adverse drug reaction (ADR) detection. This method addresses under-reporting, overcomes resource limitations, and increases ADR reporting rates in hospitals. With additional pre-training on electronic medical record (EMR) data from our health network, the model learned discharge summary formatting patterns, enabling accurate classification of relationships within these summaries.
10	Donnici 2021 (50)	Italy	Reinforcement Deep learning	We present an AIMS that assists impaired patients in taking their medications according to treatment plans. The demonstration of the AIMS through a mobile app shows promising results and has the potential to improve the quality of healthcare at home.
11	Berg 2020 (62)	United States of America	NMAM	The model proved to be highly useful in understanding how the different elements of the nurse medication administration process interact with each other. Consequently, utilizing systems-level computer simulations, such as agent-based models, can assist administrators in comprehending the impact of changes made to the medication administration process. This understanding is essential as they strive to reduce errors and enhance overall performance.
12	Dandala 2020 (63)	India	Knowledge-Aware Neural Attentive Models	This study introduces a system designed to extract drug-related concepts and their relationships, achieving better results than currently available state-of-the-art methods. It highlights how using contextualized embeddings, position-attention mechanisms, and knowledge graph embeddings can significantly enhance deep learning approaches for concept and relation extraction. Furthermore, this study illustrates the potential of deep learning methods to extract real-world evidence from unstructured patient data, contributing to drug safety surveillance.
13	Naeem 2020 (64)	Italy	medication monitoring system,CNN	We employed transfer learning techniques to train our model based on the well-known VGG-16 architecture. The trained model has demonstrated reasonable performance on both validation data and live video demonstrations. This proposed approach aims to reduce medication errors.
14	Dhokley 2020 (65)	India	Speech Recognition Natural Language Processing Stack-Propagation unidirectional LSTM self-attentive encoder	After refining our dataset and model parameters, we achieved acceptable results. This paper outlines the scope of our work and future improvement plans. Our goal is to transition from handwritten prescriptions to a more efficient and clearer mobile application, saving time and enhancing accuracy.
15	Ghasemi 2019 (66)	Iran	recommender system	Smart recommender systems can enhance the usability and safety of e-prescriptions, leading to greater adoption by physicians.

[DOI: https://doi.org/10.22034/14.1.51]

16	Chen 2019 (67)	China	clinical natural language processing (NLP) system	Our findings demonstrate that a well-designed hybrid NLP system is effective in extracting ADE and medication-related information, which can be applied in real-world scenarios to support ADE-related research and inform medical decisions.
17	Segal 2019 (53)	Israel	MedAware	A clinical decision support system employed a probabilistic machine-learning approach to detect medication errors by identifying statistically significant outliers. This system generated clinically useful alerts and demonstrated high accuracy, a low alert burden, and a low false-positive rate. Additionally, it resulted in changes to subsequent orders.
18	Roy 2019 (68)	India	Yolo and CNN and OCR	Algorithms such as You Only Look Once (YOLO), along with the effective use of convolutional neural networks and image recognition, can help create solutions to minimize errors in reading drug prescriptions. These innovations have the potential to be implemented and distributed globally.
19	Eskew 2002 (51)	United States of America	medley	Individual patients have shown immediate safety benefits. While we have yet to fully measure the impact of this infusion system on reducing IV medication errors, the preliminary data is very encouraging.

Discussion

We conducted this review in order to summarize the published information about the development and placement of AI in medication errors and the testing of AI-based tools. (69)

The comparison of the automatic dispensing system with the manual dispensing approach according to the clinical and economic results shows its advantages. The use of the automatic dispensing system reduced medication errors and medication administration time. The use of several AI tools, including BCMA and the electronic prescription system, compared to The automated dispensing system alone provides additional benefits. (70)

- The use of bar coding has an effect on the correct identification of the patient, the use of the correct medicine and the improvement of record keeping, and it can increase the safety of the patient to a great extent, and according to the survey, it reduces the error rate by 40%. Bar coding makes the distribution and administration of drugs safer. (71)
- In the comparison between clinical decision support(CDS) and machine learning system(MEDAWARE), the MedAware system has the ability to identify and prevent more errors because CDS creates only warnings that have been previously learned, errors that cannot be detected by legal approaches are identified by MedAware and 68.2% of the alerts created by MedAware are not created by other systems (MGH, CDS). 85% of the alerts created by this system are valid and 80% of the alerts are clinically useful. The MedAware system leads to a reduction in costs It is a medication error that costs more compared to CDS than the generated warnings. (72)
- The MEDLEY system enables physicians and nurses to always have an expert at the bedside. It performs a reasonableness check before medication administration, a capability that did not exist previously. The implementation of this technology was accomplished rapidly, and its success was supported by a multidisciplinary approach as well as the presence of clinical pharmacists.(51)
- Studies on medication errors reveal the need for artificial intelligence-based pill recognition systems. In this method, characters on the pill are used as information for pill recognition. This work revealed that language models in a deep learning-based pill recognition system increase the accuracy of the system and reduce the dependence of the system on the database. This study significantly improved the recognition performance compared to previous studies using a fingerprint module.(52)
- A probabilistic machine learning approach with outlier detection has been shown to reduce prescribing errors by identifying atypical medication orders from electronic health records and issuing targeted alerts. Compared to traditional rule-based CDSSs, this adaptive

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system generated far fewer alerts (0.4% vs. 37%), achieved greater clinical relevance (85% vs. 16%), and significantly influenced subsequent prescribing decisions.(53)

- A machine learning-based classifier and decision support tool was implemented to assist in coding. The system increased coding accuracy and efficiency. Approximately 150,000 emergency records were coded in less than an hour, compared to a year that would have been required manually. The system can increase injury surveillance and provide the necessary evidence for rapid decision-making. (54)

Limitations

This systematic review has several limitations that should be acknowledged. First, only studies published in English were included, which may have led to the exclusion of relevant evidence published in other languages. Additionally, the search was limited to selected electronic databases, and grey literature or unpublished data were not systematically assessed, potentially introducing publication bias. Second, the included studies showed considerable heterogeneity in study designs, AI algorithms used, data sources, and outcome measures, which limited the comparability and synthesis of findings. As this review did not perform a meta-analysis, the conclusions are based on qualitative synthesis and interpretation rather than pooled quantitative estimates. Third, many of the included studies had small sample sizes, retrospective designs, or lacked external validation, which may reduce the generalizability of their findings to real-world clinical settings. Furthermore, the rapid pace of advancement in artificial intelligence may render some of the included studies outdated as newer models and algorithms are developed. Despite these limitations, this review provides a comprehensive overview of current evidence on the role of AI in medication errors management and highlights key areas where further high-quality, prospective, and externally validated studies are needed.

Conclusion

This systematic review highlights the pivotal role of artificial intelligence (Al) in minimizing medication errors through enhanced prediction, detection, and management. Al-driven systems such as MedAware, PrescIT, and various deep learning frameworks substantially improve prescribing accuracy, patient safety, and clinical efficiency. By addressing human-related factors such as fatigue and inattention, Al supports safer medication practices. Despite its promising outcomes, issues concerning data privacy, ethical governance, and system integration remain. Overall, Al represents a transformative approach toward ensuring accurate, timely, and safe medication use within modern healthcare systems

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Ethical statement

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Conflicts of interest

The authors declare that they have no conflicts of interest. All authors contributed to writing the manuscript and approved the final version.

Highlights

What is current knowledge?

Medication errors are the most frequently occurring medical error in healthcare centers. On the other side, New computer systems and programs generally Artificial Intelligence are represented today as one of the key strategies to reduce Medication errors.

What is new here?

The use of AI and the identification of possible mistakes before they occur will significantly reduce the amount of medication errors. By using AI, it is possible to increase the accuracy of health workers, more satisfaction of patients, and save time, which is a profound transformation in the performance of treatment staff and Medicines management has created.

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Appendix: Table S1

Data base	Search formula
Pubmed	(((((((((((((((((("artificial intelligence"[All Fields]) OR ("machine learning"[All Fields])) OR ("deep learning"[All Fields])) OR ("new technologies"[All Fields])) OR ("intelligence artificial"[All Fields])) OR ("computational intelligence"[All Fields])) OR ("intelligence computational"[All Fields])) OR ("machine intelligence"[All Fields])) OR ("intelligence machine"[All Fields])) OR ("computer vision systems"[All Fields])) OR ("computer vision system"[All Fields])) OR ("knowledge acquisition"[All Fields])) OR ("knowledge representation"[All Fields])) OR ("learning machine"[All Fields])) OR ("transfer learning"[All Fields])) OR ("learning transfer"[All Fields])) OR ("learning deep"[All Fields])) OR ("hierarchical learning"[All Fields])) OR ("learning hierarchical"[All Fields])) AND (((((((((((((((((("errors medication"[All Fields]) OR ("error medication"[All Fields])) OR ("medication errors"[All Fields])) OR ("medication error"[All Fields])) OR ("look alike sound alike drug substitution errors"[All Fields])) OR ("look alike sound alike medication errors"[All Fields])) OR ("lasa medication errors"[All Fields])) OR ("lasa medication error"[All Fields])) OR ("look alike sound alike drug errors"[All Fields])) OR ("high alert drug error"[All Fields])) OR ("drug use error"[All Fields])) OR ("drug use errors"[All Fields])) OR ("adverse event"[All Fields])) OR ("prescribing error"[All Fields])) OR ("dispensing error"[All Fields])) OR

	("administration error"[All Fields])) OR ("monitoring error"[All Fields])) OR ("medication reconciliation"[All Fields])) OR ("medication error reporting"[All Fields]))
google scholar	"Artificial intelligence" AND "Medication error" "Machine learning" AND "Medication error" "Deep Learning" AND "Medication error"
sciencedirect	("Artificial intelligence" OR "Machine learning" OR "Deep Learning" OR "New technologies") AND ("medication Error" OR "Drug Use Error" OR "adverse event" OR "prescribing error" OR "Dis-Pensing error")
scopus	ALL ("Artificial intelligence" OR "Machine learning" OR "Deep Learning" OR "New technologies" OR) "Intelligence artificial" OR "computational intelligence" OR "intelligence computational" OR "machine intelligence" OR "intelligence machine" OR "computer vision systems" OR "computer vision system" OR "knowledge acquisition" OR "knowledge representation" OR "learning machine" OR "transfer learning" OR "learning transfer" OR "learning deep" OR "hierarchical learning" OR "learning hierarchical" OR "automated diagnosis" OR "computer aided diagnosis" OR "digital pathology") AND ALL ("Errors Medication" OR "Error Medication" OR "Medication errors" OR "Medication error" OR "Look-Alike Sound-Alike Drug Substitution Errors" OR "Look Alike Sound Alike Drug Substitution Errors" OR "Look-Alike Sound-Alike Medication Errors" OR "Look Alike Sound Alike Medication Errors" OR "LASA Medication Errors" OR "LASA Medication Error" OR "Look-Alike Sound-Alike Drug Errors" OR "Look Alike Sound Alike Drug Errors" OR "High-Alert Medication Errors" OR "Medication Errors High-Alert" OR "High-Alert Drug Error" OR "High Alert Drug Error" OR "Drug Use Error" OR "Drug Use Errors" OR "Adverse event" OR "Prescribing error" OR ("Dispensing error" OR "Administration error" OR "Monitoring error" OR "Medication reconciliation")
wos	1. (((((((((((((((((ALL=("artificial intelligence")) OR ALL=("machine learning")) OR ALL=("deep learning")) OR ALL=("new technologies")) OR ALL=("intelligence artificial")) OR ALL=("computational intelligence")) OR ALL=("intelligence computational")) OR ALL=("machine intelligence")) OR ALL=("intelligence machine")) OR ALL=("computer vision systems")) OR ALL=("computer vision system")) OR ALL=("knowledge acquisition")) OR ALL=("knowledge representation")) OR ALL=("learning machine")) OR ALL=("transfer learning")) OR ALL=("learning transfer")) OR ALL=("learning deep")) OR ALL=("hierarchical learning")) OR ALL=("learning hierarchical") 2. (((((((((((((((((ALL=("errors medication")) OR ALL=("error medication")) OR ALL=("medication errors")) OR ALL=("medication error")) OR ALL=("look alike sound alike drug substitution errors")) OR ALL=("look alike sound alike medication errors")) OR ALL=("lasa medication errors")) OR ALL=("lasa medication error")) OR ALL=("look alike sound alike drug errors")) OR ALL=("high alert drug error")) OR ALL=("drug use error")) OR ALL=("drug use errors")) OR ALL=("adverse event")) OR ALL=("prescribing error")) OR ALL=("dispensing error")) OR ALL=("administration error")) OR ALL=("monitoring error")) OR ALL=("medication

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		reconciliation")) OR ALL=("medication error reporting") 3. #1 AND #2 and English (Languages)
(ieee)		("All Metadata":"Artificial intelligence" OR "All Metadata":"Machine learning" OR "All Metadata":"Deep Learning" OR "All Metadata":"New technologies" OR "All Metadata":"Intelligence artificial" OR "All Metadata":"computational intelligence" OR "All Metadata":"intelligence computational" OR "All Metadata":"machine intelligence" OR "All Metadata":"intelligence machine" OR "All Metadata":"computer vision systems" OR "All Metadata":"computer vision system" OR "All Metadata":"knowledge acquisition" OR "All Metadata":"knowledge representation" OR "All Metadata":"learning machine" OR "All Metadata":"transfer learning" OR "All Metadata":"learning transfer" OR "All Metadata":"learning deep" OR "All Metadata":"hierarchical learning" OR "All Metadata":"learning hierarchical" OR "All Metadata":"automated diagnosis" OR "All Metadata":"computer aided diagnosis" OR "All Metadata":"digital pathology") AND ("All Metadata":"Errors Medication" OR "All Metadata":"Error Medication" OR "All Metadata":"Medication errors" OR "All Metadata":"Medication error" OR "All Metadata":"Look-Alike Sound-Alike Drug Substitution Errors" OR "All Metadata":"Look Alike Sound Alike Drug Substitution Errors" OR "All Metadata":"Look-Alike Sound-Alike Medication Errors" OR "All Metadata":"Look Alike Sound Alike Medication Errors" OR "All Metadata":"LASA Medication Errors" OR "All Metadata":"LASA Medication Error" OR "All Metadata":"Look-Alike Sound-Alike Drug Errors" OR "All Metadata":"Look Alike Sound Alike Drug Errors" OR "All Metadata":"High-Alert Medication Errors" OR "All Metadata":"Medication Errors High-Alert" OR "All Metadata":"High-Alert Drug Error" OR "All Metadata":"High Alert Drug Error" OR "All Metadata":"Drug Use Error" OR "All Metadata":"Drug Use Errors" OR "All Metadata":"Adverse event" OR "All Metadata":"Prescribing error" OR "All Metadata":"Dispensing error" OR "All Metadata":"Administration error" OR "All Metadata":"Monitoring error" OR "All Metadata":"Medication reconciliation")

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