**Transforming Healthcare: Reducing Medical Errors With**

**Clinical Decision Support Systems (CDSS) Utilizing A Literature Review**

Nicole Anderson, Lasya Atluri, Jyothsna Ravipalli, Aashi Sethiya, Spurthy Vupputuri

HCIP 6380: Introduction to Health Informatics

Dr. George Shaw, Jr.

December 11, 2023

**Table of Contents**

[Abstract 3](#_ms42elbvbze7)

[Introduction and Literature Review 4](#_f39tj5gaoxda)

[Data, Information, Knowledge, and Types of Analytics Needed 6](#_1b69k1j0bi0j)

[Proposed CDSS of Adverse Drug Events (AEDs) 9](#_elmdjm954buq)

[Discussion 12](#_5u1gj3i2l96l)

[Conclusion 12](#_4f1gv3do0tin)

[Section Titles and Writers 13](#_jjercgdv4ylg)

[References (APA7) 14](#_d3bx4vk8ilgd)

#### **Abstract**

Medical errors are preventable adverse events that can occur at various stages of healthcare delivery, posing risks to patient safety and well-being. Such errors, with impact ranging from mild damage to injury or death, need a thorough knowledge of their underlying causes. The multifaceted character of medical errors highlights major underlying parameters, such as communication failures between healthcare workers and patients. Human parameters like exhaustion, burnout, and insufficient training can impair decision-making and attention, while structural concerns such as defective processes and limited access to crucial information increase the chance of errors. Equipment and technology-related issues, such as malfunctions and insufficient training, are additional sources of errors. Patient-related issues, such as lack of engagement and adherence to treatment regimens, are also crucial.

Clinical Decision Support Systems (CDSS) serve a critical role in addressing the underlying causes of medical errors, providing a holistic approach to improving patient safety. CDSS works as a centralized platform for obtaining and exchanging essential patient information, minimizing the risk of errors, and miscommunications by encouraging enhanced communication among healthcare practitioners. Regarding human aspects, CDSS assists healthcare practitioners by giving real-time, evidence-based guidance, reducing cognitive burden, and providing continuous access to up-to-date clinical knowledge. CDSS connects with electronic health record systems systematically, speeding processes and finding and correcting errors, improving healthcare delivery efficiency. In terms of equipment and technology, CDSS enables real-time monitoring, alarms, and training modules, which contribute to the reduction of errors caused by equipment faults and insufficient training. CDSS systems address patient-related issues by facilitating interaction, offering instructional materials, personalized treatment regimens, and reminders to improve adherence. Furthermore, by allowing the study of reported mistakes and near-misses, CDSS helps to build a culture of continuous learning inside healthcare organizations, supporting openness, accountability, and systemic changes.

#### 

#### **Introduction and Literature Review**

**Medical Errors**

Medical errors encompass diverse events with varying levels of potential patient harm (Carver et al., 2023). Broadly defined, a medical error refers to "omission or commission in planning or execution that contributes to unintended results" (Carver et al., 2023). According to the National Academy of Medicine, formally known as the Institute of Medicine (IOM), errors are described as failures in planned actions or the use of incorrect plans to achieve specific goals, marking a shift in the perception of their rarity over the past few decades (Carver et al., 2023). These errors carry substantial consequences, leading to high morbidity, mortality, and significant economic burdens, establishing them as a pressing public health concern and a serious threat to patient safety (Carver et al., 2023). For instance, in the United States, medical mistakes are estimated to result in 44,000 to 98,000 hospital deaths annually, surpassing fatalities from motor vehicle accidents and resulting in estimated costs ranging from 37.6 to 50 billion dollars due to increased healthcare expenses, disability, and lost productivity (Carver et al., 2023).

Of the possible errors that can occur, medication errors, also known as adverse drug events (ADEs), are widely acknowledged as the most common and preventable cause of patient injury, with reported incidence rates of around 6.5 per 100 admissions in acute hospitals (Carver et al., 2023; Justinia et al., 2021). Some of the most common and preventable incidents include prescribing or dispensing the wrong dosage of a medication, drug interactions, or allergic reactions. These errors can originate from various healthcare challenges such as misapplication or lack of expertise, communication challenges in healthcare professionals between themselves or with patients, inadequate supervision, and insufficient staffing leading to overworked professionals (Rodziewicz et al., 2023).

**What is CDSS?**

A Clinical Decision Support System (CDSS) is specialized software designed to aid healthcare professionals in analyzing patient records and making informed decisions (*Clinical Decision Support System Examples,* 2020). It aims to enhance healthcare by providing clinicians with specialized clinical knowledge, patient data, and health information that can be used to formulate recommendations to clinicians and thus assist them in decision-making (Sutton et al., 2020). Nowadays, CDSSs are mainly employed at the point of care, allowing clinicians to integrate their expertise with information and suggestions offered by the CDSS (Sutton et al., 2020). Utilizing Clinical Decision Support Systems (CDSS) significantly decreases the risk of medical errors, acting as both a preventive mechanism and a valuable opinion for healthcare professionals with limited training or experience, thus mitigating common medical knowledge mix-ups (*Clinical Decision Support System Examples,* 2020).

When employed to minimize medication errors, it has demonstrated improvement in clinical outcomes by reducing prescription errors and interactions (Shahmoradi et al., 2021).

An example comes from a 2009 study of an already implemented model named HIGEA, created by the Health Research Institute of the Gregorio Marañón Hospital and discussed by Ibáñez-Garcia and their team. The meaning behind the acronym name was not provided. They evaluated the knowledge-based system that successfully prevented potential errors with 51% of alerts, with 66% of these cases requiring additional documentation due to errors in the original prescriptions (Ibáñez-Garcia et al., 2009).

Although CDSS offers numerous advantages, there exist potential challenges. Improper or inadequate implementation can limit its ability to identify medication errors or introduce new error types, putting patients at risk (*Clinical Decision Support System Examples,* 2020). Pitfalls of improper implementation include missing or outdated data within the training set or knowledge base and result in inaccurate models that recommend incorrect suggestions and make frequent, unnecessary alerts (Van Dort et al., 2020, Justinia et al., 2021). In 2021, a study investigating overrides of CDSS decisions and alerts by Justinia and their team assessed the appropriateness or reasonableness of the overrides to determine where potential errors in CDSS are. They found prevalent overrides in situations where the benefits of the medication outweighed the risks, dosages should be verified, and unverified patient allergies were present. When they delved into the causes of inappropriate overrides, it was discovered that alert fatigue was a primary cause.

Alert fatigue noted in the study is a common issue with CDSS systems where users become desensitized to alerts due to the unnecessary number of them being produced, which creates a feeling of unreliability towards the system. This distrust or insensitivity can cause users to disregard alerts without thought, causing them to miss potential accurate alerts. Justinia and the team noted an example case regarding medication dosage in a Neonatal Intensive Care Unit (NICU), which predominantly cared for premature infants. The model had solely been trained on standard care medicine, lacking any training data related to accurate dosage for premature infants. Consequently, this deficiency resulted in an under-dosage alert triggered with each dispensation, leaving nurses to ignore the system and assume their dosages were appropriate. The issue of alert fatigue was also discussed as an issue with HIGEA, with some of the causes or limitations being that some demographics were excluded due to rules or knowledge not being established for them, such as those with obesity. There also was a lack of data that could be used overall due to its inability to process natural language, meaning it could miss or wrongly alert ADEs when vital information from doctors' notes, such as diagnosis and symptoms, was not considered. The HIGEA creators combated the issue with pre-screening alerts by a pharmacist instead of the prescribing physician. This idea was backed up by a systematic review of the success of 8 models that utilized at least a clinical physician as a pre-screener, which found 5 of them to decrease redundant alerts significantly (Van Dort et al., 2020).

The following sections will continue discussing the data, information, knowledge, and types of analytics needed for CDSS. Furthermore, they will explore machine learning methods and provide expected outcomes, results, and a prototype for a proposed CDSS system. These sections will also connect the type of error or root cause CDSS can address, promising solutions to enhance healthcare services.

#### 

#### **Data, Information, Knowledge, and Types of Analytics Needed**

**Data**

Healthcare institutions gather extensive data from various sources including electronic health records (EHRs), medical imaging, laboratory tests, patient-reported outcomes, wearable devices, and more. These data encompass a wide array of patient demographics, vital signs, medical histories, diagnoses, treatments, medications, and their outcomes. Data forms the foundational layer for CDSS. The system relies on this data to provide accurate, relevant, and timely information to healthcare practitioners. It serves as the input for training and validating machine learning algorithms, which are integral to CDSS functionality. Ensuring data quality, accuracy, and interoperability across different systems is crucial. Integration of diverse datasets is essential to create a comprehensive and holistic view of patient health, enabling more accurate decision-making within CDSS. The collected data, once processed and organized, provides the basis for generating information that is used by CDSS. This information, derived from patient data, assists healthcare providers in making informed decisions by offering suggestions, alerts, reminders, or recommendations during clinical workflows.

**Information**

The rapid advancement of Artificial Intelligence, particularly Machine Learning (ML), has shown immense potential across diverse sectors, from autonomous vehicles to healthcare. However, the complexity of modern ML models, especially Deep Neural Networks, often results in opaque "black box" systems, posing challenges in understanding how predictions are made. This lack of transparency raises significant concerns, particularly in critical domains like healthcare, where the consequences of incorrect decisions are profound. While AI in medicine holds promise for personalized treatments and diagnostics, the current state faces hurdles in real-world implementation due to issues of reliability, interpretability, bias, and high false positive rates. In response, the need for Explainable AI in Clinical Decision Support Systems is paramount, aiming to provide comprehensible explanations for AI-driven decisions. Addressing this need for explainability is crucial to enhancing trust, acceptance, and usability of ML-based CDSS in healthcare, as outlined by recent research efforts seeking to bridge the gap between advanced ML models and their interpretability within medical contexts (Stiglic et al., 2020; Amann et al.,2022).

**Knowledge**

Interpretability of Machine Learning models in healthcare is critical for ensuring comprehension and trust among end-users, particularly healthcare experts. Achieving higher interpretability enables easier explanation of predictions, aiding in informed, data-driven decisions for personalized patient care. Interpretability approaches can be classified into two groups: personalized interpretation and population-level summarization. Methods can also be categorized as model-specific, tailored to interpret predictions of a specific model like neural networks, or model-agnostic, offering understandable explanations for predictions across various ML models. This overview highlights the significance of interpretability in healthcare, showcasing its practical applications in predicting health outcomes, optimizing treatments, and enhancing screening efficiency for specific conditions using structured data. Emphasizing future directions, the focus is on developing algorithmic solutions that facilitate ML-driven decision-making in high-stakes healthcare scenarios(Antoniadi et al., 2021).

**Types of Analytics**

In healthcare, traditional Clinical Decision Support Systems(CDSS) rely on established knowledge regarding medication interactions, dosages, contraindications, and patient-specific health records available in Electronic Health Records. These systems utilize structured data within EHRs, such as prescribed medications, laboratory results, diagnoses, allergies, and patient demographics. Analytics in this domain involve algorithms that examine these datasets, aiming to ensure adherence to established clinical guidelines and known best practices.

For instance, Algorithms are designed to detect potential adverse interactions between prescribed medications, alerting healthcare professionals to possible risks or contraindications based on established pharmacological knowledge (Shahmoradi et al., 2022; Jia et al.,2016). Analytics might suggest optimal dosages based on a patient's specific characteristics, such as age, weight, renal function, or comorbidities, to minimize risks associated with under or overdosing. EHR data analysis forms the backbone of decision support, providing recommendations or alerts to clinicians regarding treatment options, preventive measures, or potential risks based on historical patient data and known medical guidelines.

Further, Natural Language Processing (NLP) empowers CDSS by enabling the analysis of unstructured data, particularly textual information present in Clinical Provider Order Entry (CPOE) systems and doctor's notes. These textual sources contain vast amounts of valuable but unstructured data that hold critical insights into patient conditions, treatments, and outcomes. NLP algorithms dissect the semantics of doctor's notes, extracting valuable information about symptoms, diagnoses, treatments, and patient-specific nuances articulated in free-text form. By parsing through textual data, NLP identifies patterns, correlations, and subtle indicators that might not be easily discernible through structured data alone. This allows for the identification of trends, potential adverse events, or errors. Analyzing doctor's notes enables the extraction of individual patient nuances and complexities, empowering CDSS to provide more personalized and context-aware decision support to healthcare professionals.

These algorithms delve into unstructured clinical data, like medical records, extracting crucial information. This includes diagnoses, medications, allergies, and lab results. By readily presenting this information to clinicians, CDSS eliminates the risk of errors due to incomplete or inaccurate data. CDSS with NLP acts as vigilant guardians, constantly scanning for potential errors. When identified, these systems generate real-time alerts for clinicians. These alerts cover a broad spectrum, encompassing drug interactions, medication allergies, inappropriate dosages, and potential contraindications. Promptly addressing these alerts allows for proactive intervention, preventing errors before they have a chance to occur. NLP facilitates the seamless integration of CDSS with existing clinical workflows. This minimizes disruption and maximizes adoption within healthcare settings. By becoming an integral part of the workflow, CDSS provides context-aware support, offering relevant information and recommendations tailored to the specific patient and situation. NLP delves into vast volumes of clinical data, identifying patterns and developing predictive models. These models have the remarkable ability to forecast potential complications, disease progression, and adverse drug reactions. Armed with this knowledge, clinicians can implement preventive measures, effectively reducing the risk of errors and improving patient outcomes. NLP fosters informed patient participation by analyzing clinical notes and generating personalized communication. This can take the form of tailored messages or educational materials, empowering patients to actively engage in their healthcare decisions. Ultimately, this informed participation can lead to improved medication adherence and a reduction in medication errors.

While the potential of CDSS with NLP is undeniable, several challenges need to be addressed. Data quality and standardization are crucial, as the accuracy and effectiveness of NLP models heavily rely on reliable and consistent information. Interoperability and integration with existing healthcare IT systems are also critical for widespread adoption and optimal impact. Additionally, excessive and irrelevant alerts can lead to alert fatigue, potentially causing clinicians to disregard critical notifications. Finally, ensuring user-friendly interfaces and effective training is vital for clinicians to embrace and utilize CDSS effectively.

#### 

#### **Proposed CDSS of Adverse Drug Events (AEDs)**

Utilizing the gaps discovered during the literature review of implemented systems, the team built an evidence-based framework for a new system to prevent ADEs. We propose a prototype for knowledge and data-driven CDSS that builds off the previously mentioned systems by exploring the root causes of their issues and implementing methods to combat them. By creating an ensemble or mixed-model system, it can handle the typical knowledge-driven task required, such as alerting to possible drug interactions and associated conditions, what it is used to treat and recommend dosage from a knowledge-based, but can also utilize an NLP algorithm to pull information from doctors notes further to provide a more extensive search for possible issues but also better mitigate unwarranted alerts. Machine learning algorithms will also play a key role here in picking up trends and giving probabilities for potential ADEs.

The overarching aim of the system is to achieve comprehensive coverage to ensure its utility across diverse departments within a clinical setting like a hospital. This addresses the previously identified issue of limited usability in specific areas as highlighted in prior research. To overcome those challenges, we aim to develop a comprehensive knowledge base that is extensive in not only typical care scenarios but also critical care contexts such as intensive care units or emergency departments. We also drew from the decision rule methods used in the HIGEA model for primary medical care, our knowledge base would be constructed from the collaborative efforts of clinical pharmacists and prescribers with expertise in medications and their applications in various treatments. To ensure diversity of perspectives and expertise, prescribers will represent a variety of specialties including, for example, cardiology, oncology, and neurology. This allows for the creation of nuanced understanding beyond the generalized opinions often associated with internal medicine or non-specialty prescribers. Information that is to be collected on the medications or drugs available is their approved treatments, any standard dosage rules, known interactions, and what events or effects are known. It shall also be collected on what should and shouldn’t allow for a medication to be prescribed such as a medication not being suitable when a patient's labs are abnormal in some way or their age is not suitable such as the case with children. The structure of the knowledge base is to be done in a way that is easy to update as new information emerges. Although the initial process is time-consuming, the goal is to create a system that remains evergreen, reducing or eliminating the need for frequent rebuilding. Once the knowledge base is established, an expert system can be built utilizing the existing rules of treatment.

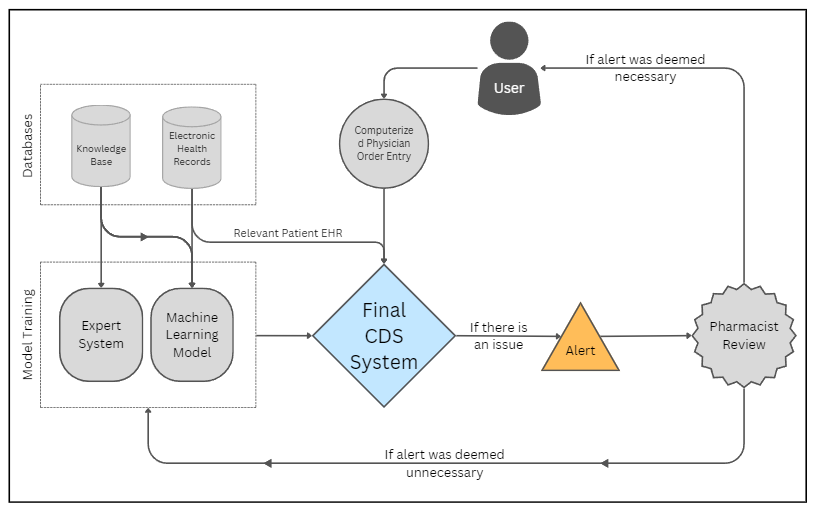
In the data-driven model, our training data will encompass a range of information found within the knowledge base created but also through available EHRs to application-oriented training. To pre-process unstructured data within doctors’ notes in EHRs, NLP techniques will be employed for effective text classification. The objective of text classification is to determine the content of the notes, including the rationale behind prescribed medication, documented side effects from past treatments, changes to treatment plans, and more. By leveraging the notes, the model can be trained with information that may be missing from the knowledge base and form new association rules for how medications may be used off-label or find noted information that is associated with ADEs. The overall machine learning algorithm to be used for classifying whether there is to be an alert and which level the alert should be is not set as no actual implementation has been tested to see which would perform the best in our case. When looking to see where success has been related to model building, Bayesian Networks implemented towards specialized ADE detection for specific conditions suggest a great starting point (Rodrigues et al., 2017, Cherkas & van Stekelenbord, 2022). When in use, the system will utilize the current patient's EHR, medication being prescribed, and any other relevant CPOE information presented through the interface, and if there is some alert, the user will receive a detailed breakdown of the issue and if the decision came from the rules or the model. This distinction will allow users and the team to understand the breakdown behind the alerts and where potential issues are commonly occurring.

To further push the model toward excellence, an implemented feature to address alert fatigue in CDSS is the differentiation of levels of alerts, distinguishing critical alerts from less urgent ones. Khalifa and Zabani inspired the concept to emphasize the importance of critical alerts and prevent them from being mistaken as less or non-critical, thereby minimizing constant interruptions that create desensitization (2016). Critical alerts would encompass those whose effects pose a threat to one's life, such as severe allergic reactions, excessive overdosage, or high-risk drug interactions. Non-urgent alerts would signal to potential harms that do not pose an immediate life-threatening or altering effect such as an increased risk of kidney or liver damage. More passive alerts would address minor things, such as the increased likelihood of experiencing adverse side effects from medications like nausea, vomiting, dizziness, or minor drug interaction. To enhance the alert distinctions, a color-coded system would be implemented to highlight on-screen alerts. Adhering to the commonly recognized alert color scheme, red will be used to distinguish critical alerts indicating urgency. Orange serves as a middle-ground color for non-urgent alerts while yellow will be used to highlight passive alerts.

With the distinction between the alerts, a refined override system can be implemented. Two different validation methods for why the override is appropriate would be provided for critical alerts: knowledgeable peer consultation or required documentation. Documentation specific to the alert, such as relevant lab or test results, would show consideration for the alert and verify that precautions were taken. Documentation can highlight potentially crucial information missing from the patient's EHR for future cases. If the case for override is frequent enough, evidence towards changes would be made in future updates to prevent the system from again being ignored and rendered useless. An example case would be a case where a patient is prescribed a drug that is life-saving for them but has immediate effects that can be damaging to the liver or kidney in a patient who already has those issues. Where the only other choice would be death, an override based on a waiver understanding of the risks would be acceptable. Without documentation, the user should get further opinions on whether the override is appropriate by another qualified professional, which can provide another level of safety in keeping those who may have a lack of experience or knowledge from single-handedly making the decision. Using the same example as before, any other doctor on the floor who would understand the state of the patient can sign off on the alert

With the idea of at least two people making the decision, another level to alleviate alert fatigue in physicians is to have a clinical pharmacist do a preliminary evaluation of the alerts. This step will occur directly after the physician puts in the order, making the pharmacist the first end-user for an alert. The pharmacist would receive the original medication order, why it is being prescribed, and the model's decision and reasoning. The pharmacist could tell if the alert would be reasonable for the physician to review as an actual issue or if it is justified and would not need any additional review. Their opinions or reasoning would also be included in the alert message to give the end user the justification for the error for them to consider, along with their additional peers' opinions when deciding the action they will take. This would also prevent a system lockup in the case of emergency medicine, with an example still being the life-saving medication mentioned earlier, as the reasoning behind why such a critical thing is being done would be stated in the original prescription and would most likely get accepted by the pharmacist as so. To better understand the overall workflow, please refer to Figure 1.

**Figure 1**

*Proposed CDSS Workflow* 

#### 

#### **Discussion**

Medical errors pose a serious risk to patient safety, often stemming from communication breakdowns, practitioner fatigue, and insufficient training (Carver et al., 2023). In response, Clinical Decision Support Systems (CDSS) emerged as a practical solution to mitigate errors.

CDSS functions as a digital assistant for healthcare professionals, offering real-time, evidence-based guidance to alleviate the complexities they face (Clinical Decision Support System Examples, 2020). It serves as a reliable tool, enhancing decision-making efficiency.

One critical area vulnerable to errors is medication prescriptions. CDSS acts as a vigilant monitor, utilizing real-time alerts and training modules to ensure accurate dosages and prevent adverse drug events (Justinia et al., 2021). It serves as a proactive measure to safeguard against medication-related errors.

To address its limitations, particularly in understanding natural language, our proposed CDSS upgrade incorporates advanced language processing (NLP). This enhancement aims to improve CDSS's understanding of doctors' notes, ultimately preventing medication-related errors more effectively (Justinia et al., 2021).In essence, CDSS is not merely a tool; it serves as a reliable partner in healthcare, streamlining processes, reducing errors, and contributing to an overall safer healthcare environment.

#### **Conclusion**

In the vast landscape of healthcare, where errors are a constant threat, Clinical Decision Support Systems (CDSS) emerge as a promising solution. As we navigate the labyrinth of medical complexities, CDSS acts as a guardian, offering a centralized platform for improved communication, real-time guidance, and error prevention.

The proposed prototype takes a step further by addressing the limitations of existing models, particularly in natural language processing. This upgrade, akin to adding a linguistic layer to CDSS, enhances its ability to understand the subtleties embedded in doctors' notes, diagnoses, and symptoms, making it a more adept tool for preventing medication-related errors (Justinia et al., 2021). In conclusion, CDSS is not just a technological innovation; it's a partner in healthcare. By seamlessly integrating into existing workflows, it enhances decision-making, reduces errors, and ultimately contributes to a safer and more efficient healthcare ecosystem.

#### 

#### **Section Titles and Writers**

| **Section Titles** | **Writer** |
| --- | --- |
| Abstract (Executive Summary) | Jyothsna Ravipalli |
| Literature Review and Introduction | Lasya Atluri |
| Data, Information, Knowledge, and Types of Analytics Needed | Spurthy Vupputuri |
| Expected Outcome, Results, and Prototypes (Proposed CDSS of Adverse Drug Events (AEDs) | Nicole Anderson |
| Conclusion and Discussion | Aashi Sethiya |

#### **References (APA7)**

Amann J, Vetter D, Blomberg SN, Christensen HC, Coffee M, Gerke S, et al. (2022) To Explain Or Not To Explain?—Artificial Intelligence Explainability In Clinical Decision Support Systems. *PLOS Digit Health,*1,2*.*<https://doi.org/10.1371/journal.pdig.0000016>

Antoniadi, A. M., Du, Y., Guendouz, Y., Wei, L., Mazo, C., Becker, B. A., & Mooney, C. (2021). Current Challenges and Future Opportunities for XAI in Machine Learning-Based Clinical Decision Support Systems: A Systematic Review. *MDPI*, *11*(11).<https://doi.org/10.3390/app11115088>

Bethany A Van Dort, Wu Yi Zheng, Vivek Sundar, Melissa T Baysari, Optimizing Clinical Decision Support Alerts In Electronic Medical Records: A Systematic Review Of Reported Strategies Adopted By Hospitals, *Journal of the American Medical Informatics Association*, Volume 28, Issue 1, January 2021, Pages 177–183,<https://doi.org/10.1093/jamia/ocaa279>

Carver, N., Gupta, V., & Hipskind, J. E. (2023, May 7). *Medical Errors*. StatPearls.<http://www.ncbi.nlm.nih.gov/books/NBK430763/>

Castaneda, C., Nalley, K., Mannion, C., Bhattacharyya, P., Blake, P., Pecora, A., Guy, A., & Suh, K. S. (2013). Clinical Decision Support Systems For Improving Diagnostic Accuracy and Achieving Precision Medicine. *National Library of Medicine*.<https://doi.org/10.1186/s13336-015-0019-3> PMID: 25834725; PMCID: PMC4381462.

Cherkas, Y., Ide, J. & van Stekelenborg, J. Leveraging Machine Learning to Facilitate Individual Case Causality Assessment of Adverse Drug Reactions. *Drug Safety* 45, 571–582 (2022). <https://doi.org/10.1007/s40264-022-01163-6>

*Clinical Decision Support System Examples – Benefits, Tools And More*. (2020, May 28). Folio3 Digital Health.<https://digitalhealth.folio3.com/blog/clinical-decision-support-system-examples-tools/>

Ibáñez-García, S., Rodríguez-González, C. G., Escudero‐Vilaplana, V., Martin-Barbero, M. L., Marzal-Alfaro, B., Rosa-Triviño, J. L. D. l., … & Sáez, M. S. (2019). Development And Evaluation Of A Clinical Decision Support System To Improve Medication Safety. *Applied Clinical Informatics*, 10(03), 513-520.<https://doi.org/10.1055/s-0039-1693426>

Jia P, Zhang L, Chen J, Zhao P, Zhang M (2016) The Effects of Clinical Decision Support Systems on Medication Safety: An Overview. *PLoS ONE*, 11, 12.<https://doi.org/10.1371/journal.pone.0167683>

Justinia, T., Qattan, W., Almenhali, A., Abo-Khatwa, A., Alharbi, O., & Alharbi, T. (2021). Medication Errors and Patient Safety: Evaluation of Physicians' Responses to Medication-Related Alert Overrides in Clinical Decision Support Systems. Acta Informatica Medica : AIM : *Journal of the Society for Medical Informatics of Bosnia & Herzegovina : casopis Drustva za medicinsku informatiku BiH*, 29(4), 248–252. <https://doi.org/10.5455/aim.2021.29.248-252>

Khalifa, M., & Zabani, I. (2016). Improving Utilization of Clinical Decision Support Systems by Reducing Alert Fatigue: Strategies and Recommendations. *Studies in Health Technology and Informatics*, 226, 51–54.

Leila, S., Reza, S., Hossein, A., & Maryam, Z. (2021). Clinical Decision Support Systems-Based Interventions To Improve Medication Outcomes: A Systematic Literature Review On Features and Effects. *National Library of Medicine*.<https://doi.org/10.47176/mjiri.35.27>

Rodrigues, P. P., Ferreira-Santos, D., Silva, A., Polónia, J., &amp; Ribeiro-Vaz, I. (2017). Implementing Guidelines For Causality Assessment Of Adverse Drug Reaction Reports: A Bayesian Network Approach. *Artificial Intelligence in Medicine*, 55–64. <https://doi.org/10.1007/978-3-319-59758-4_6>

Rodziewicz, T. L., Houseman, B., & Hipskind, J. E. (2023, May 2). Medical Error Reduction And Prevention. *StatPearls*.<http://www.ncbi.nlm.nih.gov/books/NBK499956/>

Shahmoradi, L., Safdari, R., Ahmadi, H., & Zahmatkeshan, M. (2021). Clinical Decision Support Systems-Based Interventions To Improve Medication Outcomes: A Systematic Literature Review On Features And Effects. *Medical Journal of the Islamic Republic of Iran*, 35, 27.<https://doi.org/10.47176/mjiri.35.27>

Stiglic, G., Kocbek, P., Fijacko, N., Zitnik, M., Verbert, K., & Cilar, L. (2020). Interpretability Of Machine Learning-Based Prediction Models In Healthcare. *WIREs*, *10*(5), 2.<https://wires.onlinelibrary.wiley.com/doi/epdf/10.1002/widm.1379>

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020, February 6). An Overview Of Clinical Decision Support Systems: Benefits, Risks, And Strategies For Success. *Npj Digital Medicine*.<https://doi.org/10.1038/s41746-020-0221-y>