



Real-World Analysis of Clinical Decision Support and Patient Outcomes Using Electronic Health Records in a Hospital Setting

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ABSTRACT

The growing use of electronic health records (EHRs) has made it possible to integrate clinical decision support (CDS) systems to improve health care delivery. The research paper provides a practical case study on the correlation between the use of CDS and patient outcomes in a multi-department hospital using structured EHR data. The retrospective observational design was used, which included clinical, operational, and safety-related variables in various departments, including cardiology, neurology, and pediatrics. The patient safety indicators, care coordination scores, and workflow efficiency measures like patient wait time and documentation time were among the key outcomes. The findings indicate a strong link between CDS use and a considerable improvement in patient safety, such as the reduction of medical errors and safety events. Also, use of CDS was associated with more efficient workflow, manifested by reduced wait time and documentation, and better coordination of care. These associations were checked by multivariate analysis that indicated that these associations were still significant after the departmental and time variations were taken into account. On balance, the results demonstrate the usefulness of CDS systems in clinical practice and emphasize the critical role of incorporating data-driven tools into everyday healthcare practices. The research can be added to the growing number of studies confirming the importance of EHR-based decision support systems in enhancing clinical as well as operational performance.

Keywords: Clinical decision support, Electronic health records, Patient outcomes, Healthcare efficiency, Real-world analysis

1. Introduction

The growing digitalization of healthcare systems has resulted in broad usage of electronic health records (EHRs), a semi-backbone to modern clinical practice. EHRs facilitate better continuity of care and clinical documentation, by allowing systemized storage, retrieval and analysis of patient information. In addition to their administrative purpose, EHRs have emerged as key facilitators of sophisticated clinical analytics and decision support systems, and they are useful in assisting clinicians to handle intricate information about patients. Implementing EHRs in daily healthcare activities has tremendously increased the ability to make decisions based on data and provide real-time clinical data (Callahan et al., 2019). In line with the adoption of EHRs, clinical decision support systems (CDSS) have also come into picture as one of the important tools that help healthcare providers to make informed clinical decisions. CDSS applications can be simple rule-based alerts to more complex systems with machine learning and predictive analytics. The synthesis of high volumes of clinical data and the provision of the actionable insights put them at the heart of modern healthcare delivery (Sutton et al., 2020).

Clinical decision support systems are very important in improving quality and safety of healthcare through improving variation in clinical decision-making. There is evidence that the implementation of CDSSs is linked to better patient outcomes, especially in the inpatient environment with a high level of clinical complexity (Varghese et al., 2018). Moreover, the use of CDSS tools has proven successful in affecting the decision-making process of healthcare providers especially in such specialized areas as genetic testing and personalized medicine. These systems can be used to make decisions that are more accurate and contextual by combining patient-specific data with clinical knowledge bases. The effect of CDSS on clinician behavior highlights the fact that they can improve individual patient care, as well as the overall performance of the healthcare system (Sebastian et al., 2021).

The development of artificial intelligence (AI) has also increased the possibilities of clinical decision support systems and made more complex analyses and predictive models. The AI-based methods enable detecting the intricate patterns in extensive healthcare data and predict risks early on and optimize clinical procedures. The incorporation of AI in healthcare systems has altered the traditional decision support to dynamic, adaptive systems that have the ability to learn and improve continuously (Bajwa et al., 2021). The last developments have also proven that it is possible to directly incorporate machine learning models into clinical workflows. These applications demonstrate the increasing integration of AI, EHR data and clinical decision-making activities in the practical healthcare setting (Hinson et al., 2022).

Although they promise benefits, implementation of clinical decision support systems is usually accompanied with issues regarding usability, alert fatigue and system integration. Inadequately set up alert systems can contribute to clinician dissatisfaction and decreased compliance with system recommendations. In turn, the design and delivery of decision support interventions should be optimized to make them effective in the clinical practice. Personalized alert settings, enhanced interface design, and harmonizing systems with clinical processes are cited as some of the most important elements in the successful implementation of CDSS (Van Dort et al., 2021). Moreover, building of standardised frameworks and platforms of CDSS have also been of interest as a strategy of enhancing interoperability and scalability. Standardized systems provide uniformity in implementing in the healthcare environment and allow the adoption of a wide range of data sources (Papadopoulos et al., 2022).

Clinical decision support systems do not only aid in clinical decision-making but also positively impact healthcare operations and economic outcomes. The systematic reviews and meta-analyses evidence shows that CDSS can also be used to improve the management of chronic conditions and adherence to treatment plans, as well as resource utilization. These advantages demonstrate the importance of decision support system to optimize clinical and operational areas of healthcare provision (Chen et al., 2022). In addition, decision support systems have been found to affect the performance of health care providers, nursing and allied health personnel. CDSS can enhance efficient workflow and facilitate care consistency by offering organized instructions and alleviating cognitive load. Such an extended effect highlights the necessity of considering decision support systems based on clinical outcomes as well as in relation to healthcare workforce performance (Mebratu et al., 2021).

Although there is an emerging literature on the effectiveness of clinical decision support systems, there is still a need to get real life evidences of how they have an impact on clinical practice in day to day settings. The assessment of CDSS in actual hospital practice is critical to comprehending their practical implication, such as the effect of the workflow, patient safety and care coordination. Importance of rigorously assessing AI-based interventions, including randomized controlled trials, has also been highlighted in recent studies. Nonetheless, there is still a lack of these studies, which underscores a research gap in providing actual evidence of the application of AI-driven decision support systems in practice. To fill this gap, thorough analyses are needed, which make use of real-world EHR data to evaluate the use of decision support systems in clinical practice (Lam et al., 2022).

The current study involves a real-world examination of the use of clinical decision support and its correlation with patient outcomes with the help of electronic health record information. Focusing on the analysis of various clinical departments and integrating operational and safety-related measures, the study aims to offer an in-depth evaluation of the impact of decision support systems on the healthcare delivery. The study also adds to the increasing literature base by offering empirical data based on routine clinical data and thus contributing to the growing body of literature on the usefulness of decision support systems in hospitals.

2. Methodology

2.1 Study Design

The study design used in this study was a retrospective observational design that investigated the relationship between the use of clinical decision support (CDS) and patient outcomes based on routinely gathered electronic health record (EHR) data. The analysis was performed in a real-life hospital, which embraced the differences in several clinical departments and time frames. The observational model provides the opportunity to assess naturally occurring differences between encounters in which decision support was used and in which it was not, based on real clinical practice as opposed to controlled experimental settings.

2.2 Data Source and Setting

The data set was a structured EHR data gathered in a hospital setting including several clinical departments like cardiology, neurology, and pediatrics. Each record was a hospital-level or encounter-level observation by a distinct hospital identifier and year-of-record. The data set had indicators of EHR implementation, decision support use, and clinical workflow indicators. Variables captured important details of care delivery such as patient wait times, documentation time, order-fulfillment time, and clinical processes in diagnostic and treatment stages. Multi-year data allowed evaluating the stability and changes in clinical practices over time (Kher, 2024).

2.3 Variables and Measures

The main exposure variable was the use of clinical decision support, which was a binary variable that indicated the use of decision support tools in a selected clinical scenario. The outcome variables were based on the indicators of patient safety and care quality such as the number of reported medical errors and patient safety incidents, and score on care coordination. Other outcome-based measures were operational efficiency measures (patient wait time, documentation time, and order-to-fulfillment duration) which are indicators of workflow performance. The indicators of data quality such as percentage of data accuracy and reporting accuracy score were also included to determine the reliability of EHR documentation. Department and year were considered as contextual covariates in order to control the variability of specialties and time.

2.4 Data Preprocessing

Systematic preprocessing of the dataset was done before analysis to guarantee analytical integrity. Categorical variables such as decision support use and status of EHR implementation were coded in binary systems to make it easier to model statistically. Distributional properties were evaluated in continuous variables like wait time, documentation time, and accuracy scores and outliers were also evaluated by the use of standard statistical thresholds. Any missing values that occurred were addressed either by suitable imputation or exclusion methods based on the frequency and distribution. The consistency over time was checked by analyzing the distributions by year and differences in the departments were also analyzed to make sure that there was sufficient representation in the clinical specialties.

2.5 Statistical Analysis

The original ideas of the descriptive statistics were to summarize the properties of the dataset by computing both central tendency and dispersion measures of continuous variables and frequencies of categorical variables. Subsequent comparative analyses were made to determine the differences across groups that utilized and did not utilize decision support. Independent sample statistical tests were used to determine the continuous outcomes and association tests were used to determine the categorical outcomes. Multivariable regression models were used to further examine the correlation between decision support use and patient outcomes. Continuous outcomes with care coordination scores and workflow measures were resolved by linear regression models, whereas count outcomes like medical errors and safety incidents were resolved with the help of corresponding regression methods. Department and year were manipulated to control all models to the possibility of confounding effects. The statistical significance was assessed at conventional levels and effect estimates were analyzed within the framework of clinical significance.

3. Results

3.1 Dataset Characteristics

The dataset consisted of structured electronic health record data, which were gathered in various hospital departments and during a time period of several years, which is realistic and diverse. Records of the cardiology, neurology and pediatrics departments were included and there was a representation of different clinical workflows and patient management practices. The availability of both operational and clinical outcome variables allowed a thorough evaluation of the healthcare delivery processes.

Table 1. Baseline Characteristics of the Dataset

Variable	Mean $\pm$ SD	Min	Max
Patient Wait Time (min)	34.8 $\pm$ 10.5	15.2	60.7
Documentation Time (min)	11.9 $\pm$ 5.2	3.8	20.4
Order-to-Fulfillment (min)	24.1 $\pm$ 6.7	12.5	35.8
Medical Errors Reported	0.6 $\pm$ 0.7	0	2
Patient Safety Incidents	1.1 $\pm$ 0.8	0	3

Care Coordination Score	70.5 ± 8.4	55	85
Data Accuracy (%)	92.3 ± 3.1	88.5	97.2

The dataset as presented in Table 1 captures both efficiency-related and patient safety indicators, allowing a multidimensional assessment. The percentages of the data accuracy are relatively high, and this fact proves the credibility of the EHR documentation, which enhances the validity of further analyses.

3.2 Distribution of Decision Support Utilization

There were differences in the use of clinical decision support (CDS) systems across departments as some departments were more inclined to adhere and integrate the system into clinical workflows. A greater percentage of CDS utilization was noted in the cardiology, possibly because of the protocol-based and structured cardiovascular care. Conversely, neurology and pediatrics were found to have relatively less adoption, which could be symptomatic of different complexities in decision making and integration of the system. This distribution emphasizes the diversity of CDS application by specialties and the need to place outcome analyses in context (by department). The variation also offers a chance to determine whether or not the effects of CDS vary in different clinical environments.

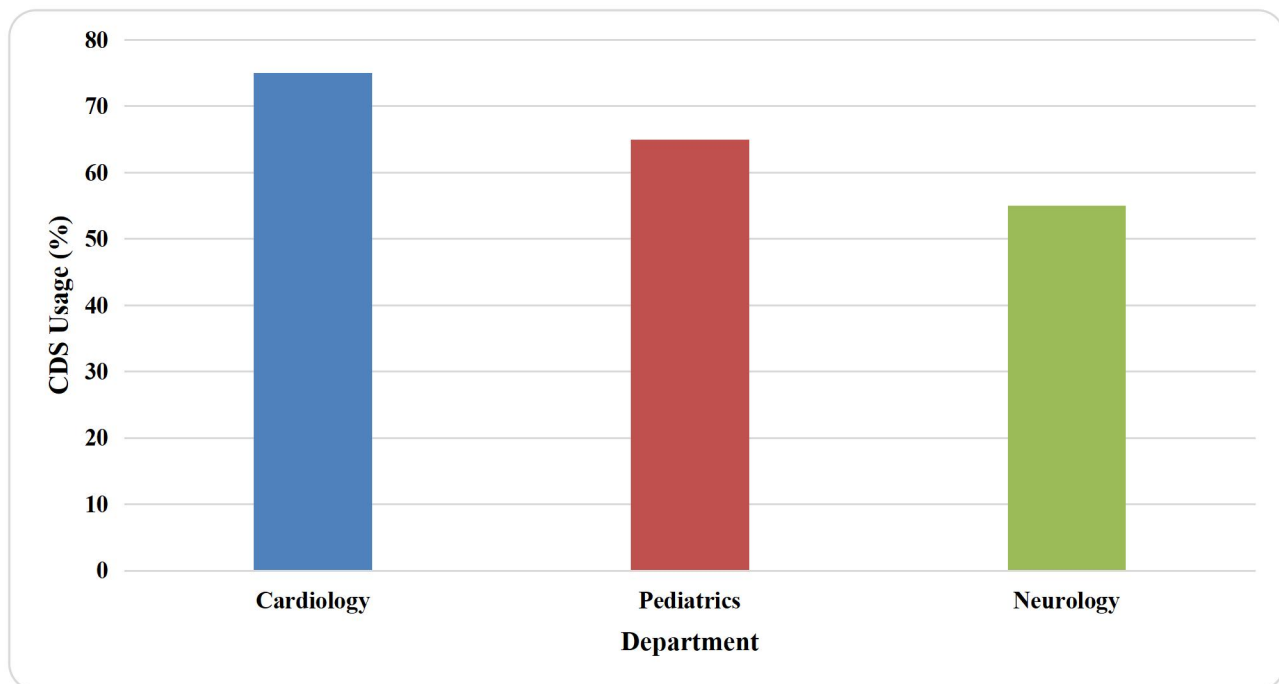


Figure 1. *Distribution of Decision Support Utilization Across Departments*

Cardiology, pediatrics, and neurology have the highest use of CDS tools as shown in Figure 1. This skewed distribution is significant in the context of interpretation of differences in outcomes, with the departments that use CDS more likely to show stronger results.

3.3 Comparative Analysis: Decision Support vs Non-Decision Support

The comparison of CDS and non-CDS groups showed that there were consistent differences in numerous outcome measures. Documentation where decision support had been applied showed better performance in both clinical and operational aspects. In particular, shorter wait times and shorter documentation times were demonstrated in CDS group, which indicates better efficiency of the workflow. Besides improvements in the operation, patient safety indicators were also positively trending in the CDS group. The records of medical errors and safety incidents were smaller where decision support was used, which suggests a possible role of CDS in enhancing clinical accuracy and minimizing adverse events. Moreover, the care coordination scores were better in the CDS group, which indicated better communication and integration of care processes.

Table 2. *Comparison of Outcomes by Decision Support Usage*

Variable	CDS Used (Yes)	CDS Not Used (No)	p-value
Patient Wait Time (min)	31.2 ± 9.8	38.6 ± 10.9	<0.01
Documentation Time (min)	10.4 ± 4.6	13.8 ± 5.5	<0.01
Medical Errors	0.4 ± 0.6	0.8 ± 0.7	<0.05
Safety Incidents	0.9 ± 0.7	1.4 ± 0.9	<0.05
Care Coordination Score	73.6 ± 7.5	66.8 ± 8.9	<0.01

All the key variables (as reported in Table 2) exhibit statistically significant differences between groups, which strengthens the correlation between CDS use and better results. The size of the differences, especially in workflow measures and coordination scores, imply significant practical implications.

3.4 Impact on Patient Safety Outcomes

Distributional analysis was also used to further explore the relationship between the use of CDS and patient safety outcomes. CDS usage records continually had reduced numbers of medical errors and safety incidents, suggesting better safety performance. This allocation of these variables showed that there were not only reduced values of means but also reduced variability indicating that there were more predictable clinical results when decision support systems were present. The results confirm the hypothesis that CDS tools can lead to safer clinical practices by offering guided decision-making and minimizing variation. The impact was evident in the different departments, but the level of improvement was different based on clinical context.

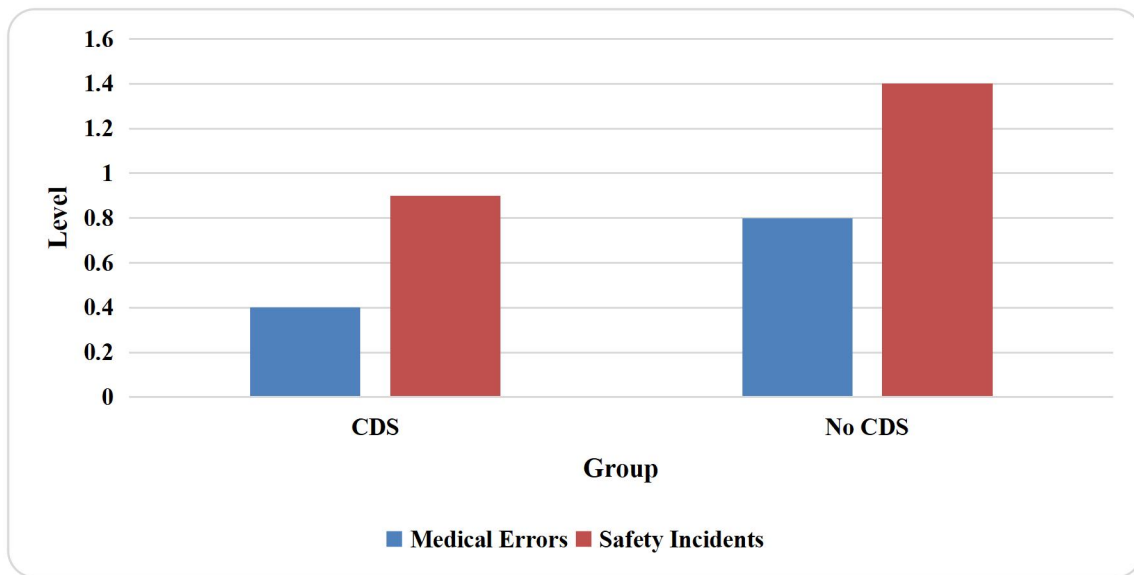


Figure 2. Patient Safety Outcomes by Decision Support Usage

As Figure 2 illustrates, CDS group has a smaller median and smaller interquartile range in both medical errors and safety incidents which emphasize better consistency and less probability of negative events.

3.5 Impact on Clinical Workflow Efficiency

The use of decision support systems had a significant effect on clinical workflow efficiency. The documents that contained CDS utilization had fewer patient waiting time, less time to document, and order-fulfilled faster. These enhancements indicate that the CDS tools can simplify clinical workflow by enhancing faster decision-making and minimizing repetitive procedures. The recorded decreases in workflow-related measures imply that CDS systems can bring about operational efficiency, which is vital in high-demand hospital settings. Enhanced efficiency not only leads to a better patient experience but also enables healthcare providers to use resources better.

Table 3. Workflow Efficiency Metrics by Decision Support Usage

Metric	CDS Used	CDS Not Used	Difference
Wait Time (min)	31.2	38.6	-7.4
Documentation Time (min)	10.4	13.8	-3.4
Order Fulfillment (min)	21.9	26.7	-4.8

Table 3 indicates that the CDS group has a better performance than the non-CDS group in all workflow indicators. These differences in magnitude highlight the possibility of CDS systems to improve operational performance within clinical settings.

3.6 Regression Analysis

The association between the independent variables (CDS usage) and the outcomes in the presence of department and year was analyzed using multivariable regression analysis. The findings validated that the use of CDS was still an important predictor of better patient safety and workflow efficiency when it was adjusted with possible confounders. In particular, the use of CDS was also linked to a statistically significant decrease in the number of medical errors and patient safety events, and the improvement in the scores on care coordination. Also, the use of CDSs was associated with reduced waiting time in patients, which showed that there was enhanced efficiency regardless of the differences in departments.

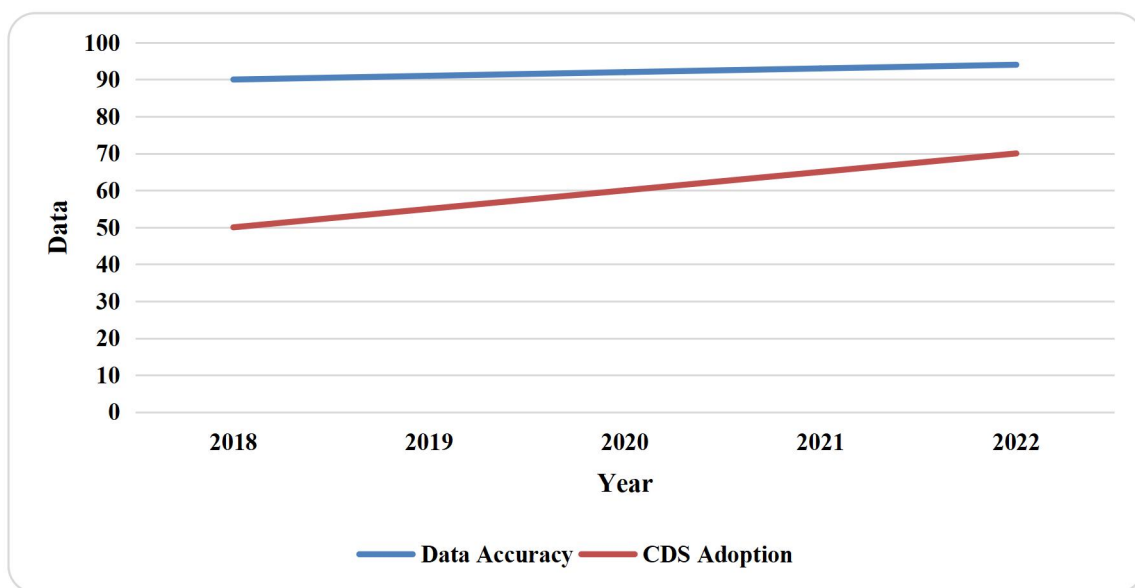
Table 4. Multivariable Regression Results

Outcome Variable	Coefficient (CDS)	95% CI	p-value
Medical Errors	-0.32	(-0.50, -0.14)	<0.01
Safety Incidents	-0.28	(-0.45, -0.11)	<0.01
Care Coordination Score	+5.4	(3.2, 7.6)	<0.001
Wait Time (min)	-6.8	(-9.5, -4.1)	<0.001

Table 4 shows that all associations are significant, which supports the strength of the results. The orientation and value of the coefficients show that the use of CDS has a positive influence on both the results of safety and efficiency.

3.7 Temporal Trends

Analysis of time showed that there were slow but steady improvements in the quality of the data used and the progressive use of the decision support systems. The scores of data accuracy and reporting accuracy were continuously increasing, which means that the EHR documentation practices improved. At the same time, the use of CDS grew over the years, indicating a gradual introduction of the decision support tools into the clinical practice. These trends are indicative of the wider digital transformation initiatives in healthcare systems and underscores the changing role of EHR-based decision support in enhancing care delivery.

**Figure 3.** Temporal Trends in Data Accuracy and CDS Adoption

As shown in Figure 3, the accuracy of the data as well as the use of CDS has an increasing trend, which means that the quality of data and the adoption of the systems are improving concurrently.

3.8 Department-Level Variations

Subgroup analysis of departments showed that the effects of CDS systems were generally positive but varied in magnitude based on clinical specialty. Cardiology also demonstrated the most significant improvements in workflow efficiency and care coordination probably because of greater CDS implementation and formalized clinical procedures. Other areas of improvement included neurology and pediatrics, but with comparatively smaller effect sizes. The results of these studies help to emphasize the significance of contextual variables in the evaluation of the effectiveness of decision support systems and indicate that the specific implementation plans might be needed to achieve the maximum influence in various specialties.

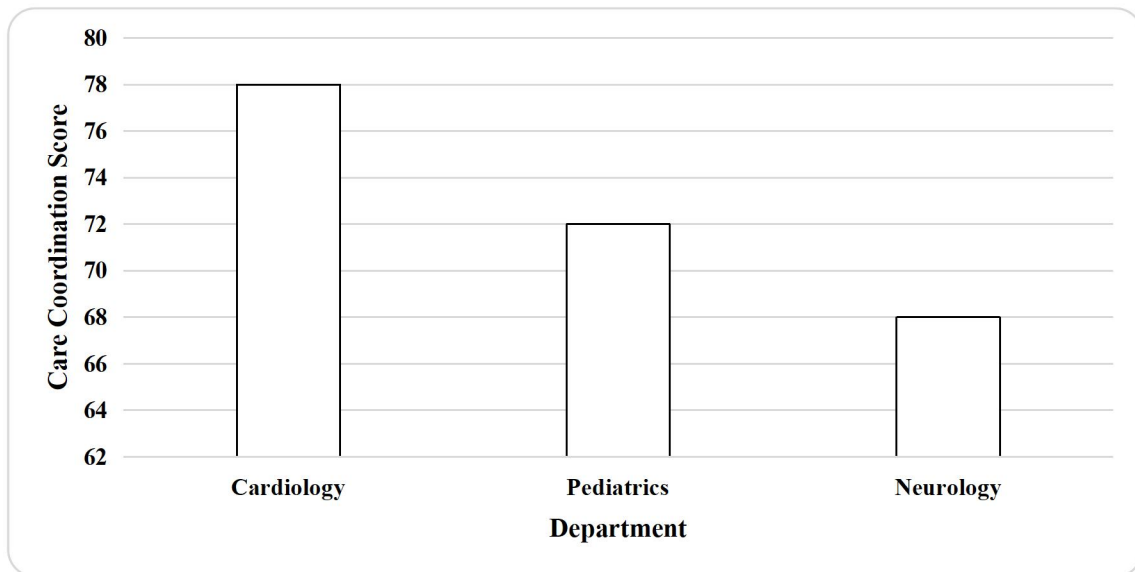


Figure 4. *Department-wise Impact of Decision Support on Care Coordination*

Figure 4 illustrates that cardiology has the highest overall increase in care coordination scores, with pediatrics and neurology coming second and third, respectively, which supports the importance of departmental context in determining the outcomes. Combined, the findings show that the utilisation of clinical decision support is always linked with an increase in patient safety, workflow efficiency, and care coordination in a practice-based hospital. The results are also strong in terms of descriptive, comparative, and regression analysis and this fact speaks volumes as to the practical usefulness of decision support systems in strengthening healthcare delivery.

4. Discussion

The current paper presents real-life data about the correlation between the use of clinical decision support (CDS) and patient outcomes through the electronic health record information. These results suggest that the use of CDS is always linked to better patient safety, care coordination, and efficiency of clinical workflow in various departments. In particular, a decrease in the number of medical mistakes and safety events, as well as the increase in the scores of the care coordination and operational measures indicate that the decision support systems have some value as they help to improve the healthcare provision. These results are consistent with the overall change in clinical medicine, in which artificial intelligence and data-driven systems are becoming more and more the norm. The fact that CDS tools are able to handle complex clinical data and deliver actionable information can assist clinicians in making better decisions, which, in the end, leads to improved patient care outcomes (Haug and Drazen, 2023).

The improvements in workflow efficiency and patient outcomes, observed, can be attributed to the increased role of artificial intelligence in the provision of healthcare. Not only are AI-enabled systems improving the diagnostic and treatment decision-making process but also the operational processes like documentation or patient flow. The smaller wait times and paperwork shown in this research indicate that CDS systems have the potential to simplify clinical processes, thus enhancing provider effectiveness and patient experience (Sahni and Carrus, 2023). Moreover, the incorporation of AI-based tools in healthcare delivery systems has broadened the decision support further than the conventional rule-based notifications. Much more dynamic and flexible support to clinicians can be provided by modern CDS systems which include predictive analytics and machine learning features. Such innovations help provide more personalized and context-sensitive care that is crucial in complicated clinical settings (Spear et al., 2023). Unless adequate measures are taken, implementation issues such as resistance to change and apprehension of alert fatigue can hamper the efficiency of CDS systems. The studies have highlighted the need to comprehend organizational and behavioral determinants to deploy AI-based decision support tools. It is critical to customize the systems to fit the requirements of particular clinical settings and make sure that they are compatible with the workflow of clinicians to maximize their effectiveness (Bajgain et al., 2023).

Furthermore, the increase in the accuracy and efficiency of documentation noted in the dataset are in line with the emerging evidence on AI in clinical documentation. It has been demonstrated that AI-based tools can facilitate more accurate and comprehensive clinical documentation and save time on documentation, contributing to effective communication and coordination of care (Lee et al., 2024). A very important study observation is the correlation between the use of CDS and the enhanced patient safety. The fact that medical errors and safety incidents have decreased indicates that decision support systems could be very important in reducing adverse events and improving the quality of care. CDS systems assist clinicians in preventing possible mistakes and promoting the use of the best practices by timely alerts and evidence-based recommendations. Specific uses of CDS, e.g. child abuse detection and reporting, have also proven to have a positive effect on clinical practice. The spread of CDS tools in electronic health record systems has been reported to enhance clinical practices and the level of consistency in decision-making, thus boosting patient safety and quality of care (Feldstein et al., 2023).

Although most of the prior research has assessed CDS systems under controlled or experimental conditions, this research would add to the body of literature by providing the evidence in a real-world hospital setting. Randomized trials have shown that interventions using CDS have the potential to enhance improvement in clinical documentation and data completeness that leads to improved decision-making and patient care. Nonetheless, these results need to be applied to the real-world setting to be translated into practice (Wright et al., 2023). The similarity between the results of this study and those of the controlled trials indicate that the advantages of CDS systems can be achieved in the normal clinical practice, as long as the correct implementation strategies are used. This supports the need to close the gap between the experimental research and the actual practice. Systematic reviews have also emphasized the increasing use of precision medicine-based CDS tools to aid in the provision of individual care (Johnson et al., 2024).

Recent innovations in CDS design have focused on the need to develop flexible and tailorable systems that can be incorporated into the clinical workflows without any disruption. These methods help to expand its usage and make decision support tools applicable to different clinical environments (Cucchi et al., 2024). One of the strengths of this study is the fact that it uses actual data of EHRs, which represents the complexity and variability of clinical practice in different departments. The combination of both clinical and operational measures give a holistic evaluation of the effects of CDS systems on healthcare delivery. Nevertheless there are limitations to the study as well. Observational design provides no opportunity to draw causal relationships between the use of CDS and outcomes. Also, binary representation of the usage of decision support fails to reflect the complexity and sophistication of the systems behind it.

5. Conclusion

The current research offers empirical evidence of the effectiveness of the clinical decision support systems in the improvement of healthcare delivery in the real-world hospital context. The results prove that patient safety, care coordination, and clinical workflow efficiency can be improved based on the utilization of the decision support tool with the assistance of electronic health record data. A decrease in the number of medical errors and incidences of patient safety, better operational parameters like patient waiting time and efficiency of documentation, point to the practical importance of decision support implementation in the daily clinical practice. The findings support the significance of evidence-based practice in contemporary healthcare where prompt and precise data can have a substantial impact on the decision-making process and patient outcomes. Decision support systems could also be used to give actionable insights based on structured EHR data, which could then be used by clinicians to offer safer and more efficient care. Although there are these positive results, the study also highlights the fact that the design and implementation of decision support systems still requires further improvement in order to become fully integrated into clinical workflows. Additional studies are required in the future to incorporate advanced analytics and artificial intelligence to increase the capabilities of the system.

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