CDSSs in cardiac surgery diagnosis

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The advances achieved in recent decades regarding cardiac surgery have led to a new risk that goes beyond surgeons' dexterity; postoperative hours are crucial for cardiac surgery patients and are usually spent in intensive care units (ICUs), where the patients need to be continuously monitored to adjust their treatment. Clinical decision support systems (CDSSs) have been developed to take this real-time information and provide clinical suggestions to physicians in order to reduce medical errors and to improve patient recovery.

Keywords: clinical decision support ; computerized physician order entry ; intensive care units ; cardiac surgery

1. Introduction

Advances in cardiac surgery have enabled the performance of these procedures in patients with the most complex cardiac pathologies and with the highest perioperative risks. These patients are likely to experience complications during the postoperative period. Cardiogenic shock (CS), low cardiac output syndrome (LCOS), stroke, kidney failure, gastrointestinal problems, and respiratory distress are the main issues that may arise during this period, entailing the highest mortality [1][2][3].

Patients undergoing heart surgery require long stays in intensive care units (ICUs), compared to other types of surgery, due to the aforementioned complications [4][5]. These include vasospasm, altered platelet–endothelial cell interactions, and a generalized inflammatory response due to blood contacting the synthetic surfaces of the bypass equipment [6][7][8]. The result is low flow in the microcirculation of the heart, brain, and other organs, which may lead to organ dysfunction [9][10]. In addition, these patients demand the use of broad resources during their stay, such as high-level surveillance and monitoring and a quick analysis of the parameters or adjustments in their medical treatment [11][12]. The assistance of vital support for these patients is made through the maintenance of vital signs in a target range, the coordination of early therapy directed by objectives in cardiogenic shock, and the hemodynamic stabilization of LCOS. These techniques can speed up postoperative recovery, decrease hospital stays or the use of mechanical ventilation, and reduce ICU days [13][14].

In ICUs, physicians must control these parameters, care for subjects' needs, and prevent complications in order to achieve the optimal conditions of these patients. Therefore, professionals must make elaborate decisions in some situations and make modifications in treatment [15][16][17]. These situations cause high pressure and intense burden that can cause medical errors and may negatively influence patients' outcomes [18][19]. According to Farzi et al., ICU patients are exposed to an average of 1.7 errors per day; specifically, medication errors represent 78% of serious medical errors [20]. The application of artificial intelligence techniques can provide support to health professionals in decision making related to the treatment of patients [21][22]. The use of clinical decision support systems (CDSSs) can be very appropriate, supporting doctors to improve the clinical progress of patients [23][24]. The development and impact of these systems in the different fields of medicine have been very important [25].

2. Background of Decision Support Systems

CDSSs are programs based on artificial intelligence (AI) and machine learning (ML) in statistical patterns [26]. CDSSs are a tool increasingly used by clinicians and can involve difficulties in understanding the logic used by AI or integrating different clinical devices [27]. CDSSs also have two other classifications: active or passive based on the design and action of the system. The temporal classification depends on the system's moment of intervention [28].

One of the main objectives of CDSSs is the analysis of patient databases, the extraction of prognostic variables, and the determination of factors to know a patient's evolution [29]. Accordingly, several studies have focused on the Medical Information Mart for Intensive Care III (MIMIC-III), being the largest free access clinical database associated with ICUs

[30]. Reports such as those by Bashar et al. have highlighted that MIMIC-III, using a large amount of data, including laboratory tests, procedures, medications, caregivers' notes, image reports, and mortality, allows us to improve relevant clinical outcomes [31][32].

Another type of CDSS focuses on patient safety and drug administration [33]. The Computerized Physician Order Entry (CPOE) offers support to avoid errors in the dosages and improves the adjustment according to a patient's comorbidities [34][35]. Databases are also important in ICUs, because they can enhance learning about the knowledge of the evolution and act in advance to prevent or act in each clinical situation [36]. Analysis of data has provided prognostic or evolutionary factors that have allowed the improvement of clinical results [37]. CDSSs can analyze different information obtained from electronic health records (EHRs) such as the sociodemographic, social, and epidemiological data of patients [38]. EHRs create alerts related to early diagnosis and trends that warn about bad prognosis indicators, allowing early modifications in treatment and modifications in clinical evolution [34][39]. CDSSs can be combined with other devices. Some studies have concluded that the combination of CDSSs and CPOE can be considered the most powerful tool for the prevention and reduction in potentially dangerous errors and for greater adjustment according to a patient's comorbidities [40][41].

Some reviews related to CDSSs have been conducted, examining the outcomes associated with CDSSs and CPOE in inpatient settings, but few have focused on the impact that these systems have on cardiac patients in ICUs. Reviews focused on cardiac patients refer only to the economic costs and benefits of CDSSs [42][43]. Another one of these reviews focused on assessing the costs of hospitalization [44]. McKibbon et al. reviewed the effectiveness of these tools on patients in ICUs [45]. Sutton et al. analyzed the benefits and risks of CDSSs under a global point of view [46]. The remaining reviews focused specifically on pediatric patients [47][48][49].

3. Discussion on Clinical decision support systems

The objectives were focused on summarizing the recent scientific evidence on this subject in order to investigate clinical decision support systems. Decision-making aids have been studied in different fields and types of patients.

The results showed an emerging area associated with the development forecast. Some studies referred to CDSSs, analyzing the predisposing parameters and supporting the forecast of the evolution and the readmission that a patient may present [50][51][52]. CDSSs use multiple parameters to determine the prognostics, such as patient characteristics, comorbidities, reasons for admission, and scales [53][54].

Specifically, the studies of Jalali et al. referred to the prediction of development in said studies. Both studies focused on patients with neurocritical and periventricular leukomalacia patients. They reported that a rapid prediction of a patient's development can reduce mortality levels or hospital stay, among others [53][50].

The databases through CDSSs, including the parameters, proved their usefulness in predicting evolution, such as demographic data, laboratory data, and admission diagnoses [55][51]. Some reviews support the above. These reviews focused extensively on analyzing the prediction ranges of tools such as databases or CDSSs [56][57].

Another result that emerged strongly in the selected articles was medical errors. Specifically, the tools applied to CPOE systems were assessed in relation to their strong impact on the prevention of drug-related errors [58][59][60][61]. According to the evidence, CPOE tools prevent the wrong administration of drugs and help to make dosage adjustments considering comorbidities, which are among the most common confounding factors [62][63][64]. These dose modifications could eventually lead to a reduction in critical events such as cardiorespiratory arrest [61].

In addition, the results indicate that drug administration times were significantly reduced after the use of CPOE. Among the studies that were analyzed, the improvement in healthcare after the use of CPOE is meaningful, since errors of administration were recorded before and after its application, and a reduction was observed [58][59][60][61]. The reduction in the incidence of drug administration errors and the reduction in time to administration is of paramount importance in the pandemic situation because of the shortage in resources in critical care settings, and it must not be overlooked [65][66]. Although this situation does not directly affect the tasks usually performed by physicians or nursing professionals, it is considered one of the most limiting factors in providing the necessary care on time, so any tool capable of alleviating burdens should be considered potentially useful [64].

Moreover, the results suggest that these tools can detect difficulties in a patient's situation for rapid action [67][68][69]. Considering the evidence, CDSSs and EHRs allow continuous monitoring for detecting clinical alterations at the precise moment they take place. This is relevant in postoperative patients, as they have a greater risk of suffering significant complications [65].

CDSSs also offer a precise adjustment of dosage or flux to maintain a variable in the desired range [70][71][72][67][73][74]. Some examples of the already developed CDSSs on this subject matter belong to the field of hemodynamic advanced measurement devices, such as cardiac output (CO) [72][73]. These studies dealt with the utilization of a CDSS combined with a continuous monitor of cardiovascular function [71][67]. The systems were able to select and advise reasonable treatments under different clinical conditions [70].

These systems are able to select and advise reasonable treatments under different clinical conditions. However, some of the analyzed results showed no significant statistical differences, and the lack of significant differences should not impede the relevance of these findings [74]. It is remarkable to find such high concordance between specialists trained in intensive care and decision support systems and their ability to reach an equivalent fluid balance. As mentioned before, any tool with the ability to perform successfully while keeping high standards of care must be considered potentially useful, since it may allow dedicating human resources to more sophisticated tasks in healthcare.

Finally, the degree of acceptance of systems that report high levels of acceptance was evaluated for these systems for treatment and diagnosis [75][76] Other studies have considered it negative in terms of a lack of confidence in the decisions suggested, as occurs in nursing staff, about the regulation of glucose levels by prolonging the time to accept or reject the suggestion, concluding that these tools represent low impact on their work activities [59]. Doubt then arises about whether the correct implementation of CDSSs, despite their initial investment, guarantees a cost reduction at any hospital, as the shorter the patient needs to stay in ICUs, the lower amount of money will be necessary to invest.

References

1. Elgharably, H.; Gamaleldin, M.; Ayyat, K.S.; Zaki, A.; Hodges, K.; Kindzelski, B.; Yongue, C.; de la Serna, S.; Perez, J.; Spencer, C.; et al. Serious Gastrointestinal Complications after Cardiac Surgery & Associated Mortality. Ann. Thorac. Surg. 2020.
2. Tanner, T.G.; Colvin, M.O. Pulmonary Complications of Cardiac Surgery. Lung 2020, 198, 889–896.
3. Ghannem, M.; Ahmaidi, S.; Ghannem, L.; Meimoun, P. Infectious and inflammatory complications occurring after cardiac surgery in cardiac rehabilitation centres. Ann. Cardiol. Angeiol. (Paris) 2020, 69, 424–429.
4. Hassan, A.; Anderson, C.; Kypson, A.; Kindell, L.; Ferguson, T.B.; Chitwood, W.R.; Rodriguez, E. Clinical Outcomes in Patients With Prolonged Intensive Care Unit Length of Stay After Cardiac Surgical Procedures. Ann. Thorac. Surg. 2012, 93, 565–569.
5. Silberman, S.; Bitran, D.; Fink, D.; Tauber, R.; Merin, O. Very Prolonged Stay in the Intensive Care Unit After Cardiac Operations: Early Results and Late Survival. Ann. Thorac. Surg. 2013, 96, 15–22.
6. Cho, Y.J.; Nam, K.; Yoo, S.J.; Lee, S.; Bae, J.; Park, J.-Y.; Kim, H.-R.; Kim, T.K.; Jeon, Y. Effects of remote ischemic preconditioning on platelet activation and reactivity in patients undergoing cardiac surgery using cardiopulmonary bypass: A randomized controlled trial. Platelets 2020, 1–9.
7. Vedel, A.G.; Holmgaard, F.; Rasmussen, L.S.; Langkilde, A.; Paulson, O.B.; Lange, T.; Thomsen, C.; Olsen, P.S.; Ravn, H.B.; Nilsson, J.C. High-target versus low-target blood pressure management during cardiopulmonary bypass to prevent cerebral injury in cardiac surgery patients: A randomized controlled trial. Circulation 2018, 137, 1770–1780.
8. Abrard, S.; Fouquet, O.; Riou, J.; Rineau, E.; Abraham, P.; Sargentini, C.; Bigou, Y.; Baufreton, C.; Lasocki, S.; Henni, S. Preoperative endothelial dysfunction in cutaneous microcirculation is associated with postoperative organ injury after cardiac surgery using extracorporeal circulation: A prospective cohort study. Ann. Intensive Care 2021, 11, 4.
9. Rossaint, J.; Berger, C.; Van Aken, H.; Scheld, H.H.; Zahn, P.K.; Rukosujew, A.; Zarbock, A. Cardiopulmonary Bypass during Cardiac Surgery Modulates Systemic Inflammation by Affecting Different Steps of the Leukocyte Recruitment Cascade. PLoS ONE 2012, 7, e45738.
10. Itagaki, S.; Chikwe, J.P.; Chiang, Y.P.; Egorova, N.N.; Adams, D.H. Long-Term Risk for Aortic Complications After Aortic Valve Replacement in Patients With Bicuspid Aortic Valve Versus Marfan Syndrome. J. Am. Coll. Cardiol. 2015, 65, 2363–2369.
11. Arora, R.C.; Chatterjee, S.; Shake, J.G.; Hirose, H.; Engelman, D.T.; Rabin, J.; Firstenberg, M.; Moosdorf, R.G.H.; Geller, C.M.; Hiebert, B.; et al. Survey of Contemporary Cardiac Surgery Intensive Care Unit Models in the United States. Ann. Thorac. Surg. 2020, 109, 702–710.
12. Benoit, M.A.; Bagshaw, S.M.; Norris, C.M.; Zibdawi, M.; Chin, W.D.; Ross, D.B.; Van Diepen, S. Postoperative complications and outcomes associated with a transition to 24/7 intensivist management of cardiac surgery patients.

Crit. Care Med. 2017, 45, 993–1000.

13. Kumar, K.; Zarychanski, R.; Bell, D.D.; Manji, R.; Zivot, J.; Menkis, A.H.; Arora, R.C. Impact of 24-Hour In-House Intensivists on a Dedicated Cardiac Surgery Intensive Care Unit. Ann. Thorac. Surg. 2009, 88, 1153–1161.
14. Rahmanian, P.B.; Kröner, A.; Langebartels, G.; Özel, O.; Wippermann, J.; Wahlers, T. Impact of major non-cardiac complications on outcome following cardiac surgery procedures: Logistic regression analysis in a very recent patient cohort. Interact. Cardiovasc. Thorac. Surg. 2013, 17, 319–327.
15. Pimentel, M.F.; Soares, M.J.F.; Junior, J.A.M.; de Oliveira, M.A.B.; Faria, F.L.; Faveri, V.Z.; Iano, Y.; Guido, R.C. Predictive Factors of Long-Term Stay in the ICU after Cardiac Surgery: Logistic CASUS Score, Serum Bilirubin Dosage and Extracorporeal Circulation Time. Braz. J. Cardiovasc. Surg. 2017, 32, 367–371.
16. Albanesi, B.; Nania, T.; Barello, S.; Villa, G.; Rosa, D.; Caruso, R.; Udugampolage, N.S.; Casole, L.; Dellafiore, F. Lived experience of patients in after cardiac surgery: A phenomenological study. Nurs. Crit. Care 2020.
17. Kolat, P.; Guttenberger, P.; Ried, M.; Kapahnke, J.; Haneya, A.; Schmid, C.; Diez, C. ICU Readmission after Cardiac Surgery—Still a Matter of Concern? Thorac. Cardiovasc. Surg. 2020, 68, 384–388.
18. Latif, A.; Kruer, R.; Jarrell, A. Reducing medication errors in critical care: A multimodal approach. Clin. Pharmacol. Adv. Appl. 2014, 6, 117–126.
19. Martinez, E.A.; Shore, A.; Colantuoni, E.; Herzer, K.; Thompson, D.A.; Gurses, A.P.; Marsteller, J.A.; Bauer, L.; Goeschel, C.A.; Cleary, K.; et al. Cardiac surgery errors: Results from the UK National Reporting and Learning System. Int. J. Qual. Heal. Care 2011, 23, 151–158.
20. Farzi, S.; Irajpour, A.; Saghaei, M.; Ravaghi, H. Causes of medication errors in intensive care units from the perspective of healthcare professionals. J. Res. Pharm. Pract. 2017, 6, 158–165.
21. Martínez-Romero, M.; Vázquez-Naya, J.M.; Pereira, J.; Pereira, M.; Pazos, A.; Baños, G. The iOSC3 System: Using Ontologies and SWRL Rules for Intelligent Supervision and Care of Patients with Acute Cardiac Disorders. Comput. Math. Methods Med. 2013, 2013, 650671.
22. Chi, C.-L.; Street, W.N.; Katz, D.A. A decision support system for cost-effective diagnosis. Artif. Intell. Med. 2010, 50, 149–161.
23. Kindle, R.D.; Badawi, O.; Celi, L.A.; Sturland, S. Intensive Care Unit Telemedicine in the Era of Big Data, Artificial Intelligence, and Computer Clinical Decision Support Systems. Crit. Care Clin. 2019, 35, 483–495.
24. Schuh, C.; de Bruin, J.S.; Seeling, W. Clinical decision support systems at the Vienna General Hospital using Arden Syntax: Design, implementation, and integration. Artif. Intell. Med. 2018, 92, 24–33.
25. Fernandes, M.; Vieira, S.M.; Leite, F.; Palos, C.; Finkelstein, S.; Sousa, J.M.C. Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: A Review. Artif. Intell. Med. 2020, 102, 101762.
26. Johnson, A.E.W.; Ghassemi, M.M.; Nemati, S.; Niehaus, K.E.; Clifton, D.; Clifford, G.D. Machine Learning and Decision Support in Critical Care. Proc. IEEE 2016, 104, 444–466.
27. Sidey-Gibbons, J.A.M.; Sidey-Gibbons, C.J. Machine learning in medicine: A practical introduction. BMC Med. Res. Methodol. 2019, 19, 64.
28. Osheroff, J. Improving Outcomes with Clinical Decision Support; HIMSS Publishing: Boca Ratón, FL, USA, 2012; ISBN 9781498757461.
29. Tygesen, H.; Eriksson, H.; Herlitz, J. Clinical decision support system (CDSS)—Effects on care quality. Int. J. Health Care Qual. Assur. 2014, 27, 707–718.
30. Fan, Y.; Zhao, Y.; Li, P.; Liu, X.; Jia, L.; Li, K.; Feng, C.; Pan, F.; Li, T.; Zhang, Z.; et al. Analysis of diseases distribution in Medical Information Mart for Intensive Care III database. Zhonghua Wei Zhong Bing Ji Jiu Yi Xue 2018, 30, 531–537.
31. Celi, L.; Hinske, L.C.; Alterovitz, G.; Szolovits, P. An artificial intelligence tool to predict fluid requirement in the intensive care unit: A proof-of-concept study. Crit. Care 2008, 12, R151.
32. Bashar, S.K.; Hossain, M.B.; Ding, E.; Walkey, A.J.; McManus, D.D.; Chon, K.H. Atrial Fibrillation Detection During Sepsis: Study on MIMIC III ICU Data. IEEE J. Biomed. Heal. Inform. 2020, 24, 3124–3135.
33. Lin, C.-P.; Payne, T.H.; Nichol, W.P.; Hoey, P.J.; Anderson, C.L.; Gennari, J.H. Evaluating Clinical Decision Support Systems: Monitoring CPOE Order Check Override Rates in the Department of Veterans Affairs' Computerized Patient Record System. J. Am. Med. Inform. Assoc. 2008, 15, 620–626.
34. Wong, A.; Amato, M.G.; Seger, D.L.; Rehr, C.; Wright, A.; Slight, S.P.; Beeler, P.E.; Orav, E.J.; Bates, D.W. Prospective evaluation of medication-related clinical decision support over-rides in the intensive care unit. BMJ Qual. Saf. 2018, 27, 718–724.

35. Cresswell, K.; Mozaffar, H.; Shah, S.; Sheikh, A. Approaches to promoting the appropriate use of antibiotics through hospital electronic prescribing systems: A scoping review. Int. J. Pharm. Pract. 2017, 25, 5–17.

36. Stultz, J.S.; Nahata, M.C. Computerized clinical decision support for medication prescribing and utilization in pediatrics. J. Am. Med. Inform. Assoc. 2012, 19, 942–953.

37. Jin, B.; Che, C.; Liu, Z.; Zhang, S.; Yin, X.; Wei, X. Predicting the Risk of Heart Failure With EHR Sequential Data Modeling. IEEE Access 2018, 6, 9256–9261.

38. Dias, D.; Paulo Silva Cunha, J. Wearable Health Devices—Vital Sign Monitoring, Systems and Technologies. Sensors 2018, 18, 2414.

39. Downing, N.L.; Rolnick, J.; Poole, S.F.; Hall, E.; Wessels, A.J.; Heidenreich, P.; Shieh, L. Electronic health record-based clinical decision support alert for severe sepsis: A randomised evaluation. BMJ Qual. Saf. 2019, 28, 762–768.

40. Prgomet, M.; Li, L.; Niazkhani, Z.; Georgiou, A.; Westbrook, J.I. Impact of commercial computerized provider order entry (CPOE) and clinical decision support systems (CDSSs) on medication errors, length of stay, and mortality in intensive care units: A systematic review and meta-analysis. J. Am. Med. Inform. Assoc. 2017, 24, 413–422.

41. Vermeulen, K.M.; van Doormaal, J.E.; Zaal, R.J.; Mol, P.G.M.; Lenderink, A.W.; Haaijer-Ruskamp, F.M.; Kosterink, J.G.W.; van den Bemt, P.M.L.A. Cost-effectiveness of an electronic medication ordering system (CPOE/CDSS) in hospitalized patients. Int. J. Med. Inform. 2014, 83, 572–580.

42. Jacob, V.; Thota, A.B.; Chattopadhyay, S.K.; Njie, G.J.; Proia, K.K.; Hopkins, D.P.; Ross, M.N.; Pronk, N.P.; Clymer, J.M. Cost and economic benefit of clinical decision support systems for cardiovascular disease prevention: A community guide systematic review. J. Am. Med. Inform. Assoc. 2017, 24, 669–676.

43. Njie, G.J.; Proia, K.K.; Thota, A.B.; Finnie, R.K.C.; Hopkins, D.P.; Banks, S.M.; Callahan, D.B.; Pronk, N.P.; Rask, K.J.; Lackland, D.T.; et al. Clinical Decision Support Systems and Prevention. Am. J. Prev. Med. 2015, 49, 784–795.

44. Fillmore, C.L.; Bray, B.E.; Kawamoto, K. Systematic review of clinical decision support interventions with potential for inpatient cost reduction. BMC Med. Inform. Decis. Mak. 2013, 13.

45. Ann McKibbon, K.; Lokker, C.; Handler, S.M.; Dolovich, L.R.; Holbrook, A.M.; O'Reilly, D.; Tamblyn, R.; Hemens, B.J.; Basu, R.; Troyan, S.; et al. The effectiveness of integrated health information technologies across the phases of medication management: A systematic review of randomized controlled trials. J. Am. Med. Informatics Assoc. 2012, 19, 22–30.

46. Sutton, R.T.; Pincock, D.; Baumgart, D.C.; Sadowski, D.C.; Fedorak, R.N.; Kroeker, K.I. An overview of clinical decision support systems: Benefits, risks, and strategies for success. npj Digit. Med. 2020, 3, 17.

47. Chuo, J.; Hicks, R.W. Computer-Related Medication Errors in Neonatal Intensive Care Units. Clin. Perinatol. 2008, 35, 119–139.

48. MacK, E.H.; Wheeler, D.S.; Embi, P.J. Clinical decision support systems in the pediatric intensive care unit. Pediatr. Crit. Care Med. 2009, 10, 23–28.

49. York, J.B.; Cardoso, M.Z.; Azuma, D.S.; Beam, K.S.; Binney, G.G.; Weingart, S.N. Computerized Physician Order Entry in the Neonatal Intensive Care Unit: A Narrative Review. Appl. Clin. Inform. 2019, 10, 487–494.

50. Jalali, A.; Simpao, A.F.; Gálvez, J.A.; Licht, D.J.; Nataraj, C. Prediction of Periventricular Leukomalacia in Neonates after Cardiac Surgery Using Machine Learning Algorithms. J. Med. Syst. 2018, 42, 177.

51. Saeed, M.; Villarroel, M.; Reisner, A.T.; Clifford, G.; Lehman, L.-W.; Moody, G.; Heldt, T.; Kyaw, T.H.; Moody, B.; Mark, R.G. Multiparameter Intelligent Monitoring in Intensive Care II: A public-access intensive care unit database. Crit. Care Med. 2011, 39, 952–960.

52. Rojas, J.C.; Carey, K.A.; Edelson, D.P.; Venable, L.R.; Howell, M.D.; Churpek, M.M. Predicting Intensive Care Unit Readmission with Machine Learning Using Electronic Health Record Data. Ann. Am. Thorac. Soc. 2018, 15, 846–853.

53. Jalali, A.; Bender, D.; Rehman, M.; Nadkanri, V.; Nataraj, C. Advanced analytics for outcome prediction in intensive care units. In Proceedings of the 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 16–20 August 2016; pp. 2520–2524.

54. Khalifa, M.; Magrabi, F.; Gallego, B. Developing a framework for evidence-based grading and assessment of predictive tools for clinical decision support. BMC Med. Inform. Decis. Mak. 2019, 19, 207.

55. Kallet, R.H.; Branson, R.D. Respiratory controversies in the critical care setting. Do the NIH ARDS Clinical Trials Network PEEP/FIO2 tables provide the best evidence-based guide to balancing PEEP and FIO2 settings in adults? Respir. Care 2007, 52, 461–475; discussion 475–477.

56. Myssiorek, D.; Ahmed, Y.; Parsikia, A.; Castaldi, M.; McNelis, J. Factors predictive of the development of surgical site infection in thyroidectomy—An analysis of NSQIP database. Int. J. Surg. 2018, 60, 273–278.

57. Wessler, B.S.; Lai YH, L.; Kramer, W.; Cangelosi, M.; Raman, G.; Lutz, J.S.; Kent, D.M. Clinical Prediction Models for Cardiovascular Disease. Circ. Cardiovasc. Qual. Outcomes 2015, 8, 368–375.

58. Warrick, C.; Naik, H.; Avis, S.; Fletcher, P.; Franklin, B.D.; Inwald, D. A clinical information system reduces medication errors in paediatric intensive care. Intensive Care Med. 2011, 37, 691–694.

59. Armada, E.R.; Villamañán, E.; López-de-Sá, E.; Rosillo, S.; Rey-Blas, J.R.; Testillano, M.L.; Álvarez-Sala, R.; López-Sendón, J. Computerized physician order entry in the cardiac intensive care unit: Effects on prescription errors and workflow conditions. J. Crit. Care 2014, 29, 188–193.

60. Gouyon, B.; Iacobelli, S.; Saliba, E.; Quantin, C.; Pignolet, A.; Jacqz-Aigrain, E.; Gouyon, J.B. A Computer Prescribing Order Entry-Clinical Decision Support system designed for neonatal care: Results of the 'preselected prescription' concept at the bedside. J. Clin. Pharm. Ther. 2017, 42, 64–68.

61. Vardi, A.; Efrati, O.; Levin, I.; Matok, I.; Rubinstein, M.; Paret, G.; Barzilay, Z. Prevention of potential errors in resuscitation medications orders by means of a computerised physician order entry in paediatric critical care. Resuscitation 2007, 73, 400–406.

62. Elshayib, M.; Pawola, L. Computerized provider order entry–related medication errors among hospitalized patients: An integrative review. Health Inform. J. 2020, 26, 2834–2859.

63. Manias, E.; Kusljic, S.; Wu, A. Interventions to reduce medication errors in adult medical and surgical settings: A systematic review. Ther. Adv. Drug Saf. 2020, 11, 204209862096830.

64. Kinlay, M.; Zheng, W.Y.; Burke, R.; Juraskova, I.; Moles, R.; Baysari, M. Medication errors related to computerized provider order entry systems in hospitals and how they change over time: A narrative review. Res. Soc. Adm. Pharm. 2020.

65. Sutherland, A.; Canobbio, M.; Clarke, J.; Randall, M.; Skelland, T.; Weston, E. Incidence and prevalence of intravenous medication errors in the UK: A systematic review. Eur. J. Hosp. Pharm. 2020, 27, 3–8.

66. Hosseini-Marznaki, Z.; Pouy, S.; Salisu, W.J.; Emami Zeydi, A. Medication errors among Iranian emergency nurses: A systematic review. Epidemiol. Health 2020, 42, e2020030.

67. Hsu, J.-C.; Chen, Y.-F.; Chung, W.-S.; Tan, T.-H.; Chen, T.; Chiang, J.Y. Clinical Verification of A Clinical Decision Support System for Ventilator Weaning. Biomed. Eng. Online 2013, 12, S4.

68. Zaslansky, R.; Rothaug, J.; Chapman, R.C.; Backström, R.; Brill, S.; Engel, C.; Fletcher, D.; Fodor, L.; Funk, P.; Gordon, D.; et al. PAIN OUT: An international acute pain registry supporting clinicians in decision making and in quality improvement activities. J. Eval. Clin. Pract. 2014, 20, 1090–1098.

69. Aushev, A.; Ripoll, V.R.; Vellido, A.; Aletti, F.; Pinto, B.B.; Herpain, A.; Post, E.H.; Medina, E.R.; Ferrer, R.; Baselli, G.; et al. Feature selection for the accurate prediction of septic and cardiogenic shock ICU mortality in the acute phase. PLoS ONE 2018, 13, e0199089.

70. Banner, M.J.; Euliano, N.R.; MacIntyre, N.R.; Layon, A.J.; Bonett, S.; Gentile, M.A.; Bshouty, Z.; Peters, C.; Gabrielli, A. Ventilator Advisory System Employing Load and Tolerance Strategy Recommends Appropriate Pressure Support Ventilation Settings. Chest 2008, 133, 697–703.

71. Campion, T.R.; May, A.K.; Waitman, L.R.; Ozdas, A.; Lorenzi, N.M.; Gadd, C.S. Characteristics and effects of nurse dosing over-rides on computer-based intensive insulin therapy protocol performance. J. Am. Med. Inform. Assoc. 2011, 18, 251–258.

72. Denaï, M.A.; Mahfouf, M.; Ross, J.J. A hybrid hierarchical decision support system for cardiac surgical intensive care patients. Part I: Physiological modelling and decision support system design. Artif. Intell. Med. 2009, 45, 35–52.

73. Ross, J.J.; Denaï, M.A.; Mahfouf, M. A hybrid hierarchical decision support system for cardiac surgical intensive care patients. Part II. Clinical implementation and evaluation. Artif. Intell. Med. 2009, 45, 53–62.

74. Sondergaard, S.; Wall, P.; Cocks, K.; Parkin, W.G.; Leaning, M.S. High concordance between expert anaesthetists' actions and advice of decision support system in achieving oxygen delivery targets in high-risk surgery patients. Br. J. Anaesth. 2012, 108, 966–972.

75. Sintchenko, V.; Coiera, E. Decision complexity affects the extent and type of decision support use. In AMIA Annual Symposium Proceedings; American Medical Informatics Association: Bethesda, MD, USA, 2006; pp. 724–728.

76. Thompson, B.T.; Orme, J.F.; Zheng, H.; Luckett, P.M.; Truwit, J.D.; Willson, D.F.; Hite, R.D.; Brower, R.G.; Bernard, G.R.; Curley, M.A.Q.; et al. Multicenter Validation of a Computer-Based Clinical Decision Support Tool for Glucose Control in Adult and Pediatric Intensive Care Units. J. Diabetes Sci. Technol. 2008, 2, 357–368.