

Influence of Changes in Vital Signs on the Prediction of Adverse Events in Hospitalized Patients

by

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Abstract

Background: In-hospital cardiac arrest (IHCA) is the most serious adverse event in hospitalized patients, and how to identify patients at risk has been studied for many years. Various activation criteria for a rapid response systems (RRS) have been created to predict adverse events, but most of the criteria have only been based on on-the-spot values of vital signs and did not reflect trends in vital signs over time. The prevalence and details of changes in vital signs before the occurrence of adverse events are not yet well known. We therefore investigated the influence of changes in vital signs on the prediction of adverse events among hospitalized patients.

Methods: A retrospective observational study was conducted at a single center targeting adult hospitalized patients from January to December 2019. The primary outcome was the composite outcome of unexpected cardiac arrest and unplanned ICU admission. Five fundamental vital signs were used: heart rate (HR), systolic blood pressure (SBP), respiratory rate (RR), peripheral oxygen saturation level (SpO₂), and body temperature (Temp), and the worst values before the outcome and the delta values(Δ) were obtained. A delta value(Δ) is the difference between the worst value prior to the outcome and the baseline value. The relationship between the worst values and the Δ values was first described for cases that experienced the primary outcome. These were then compared with the control using logistic regression analysis. Multivariate analysis was finally performed to build three different models, and the area under the receiver operating characteristic curve (AUC) was used to demonstrate the prediction power of adverse events in the hospital.

Results: Among 24,509 newly admitted patients during the study period, 156 patients experienced 161 adverse events. Among them, both the worst values and the Δ values were obtained for SBP in 98 cases, HR in 95 cases, RR in 65 cases, SpO₂ in 72 cases, and Temp in

94 cases. The number of patients who met the single parameter criteria for RRS activation was 27/98 (27.6%) for SBP, 19/95 (20%) for HR, 21/65 (32.3%) for RR, and 11/72 (15.3%) for SpO₂. However, by adding Δ value to the criteria of these four vital signs, 6 (6.1%), 13 (13.7%), 7 (10.8%), and 11 (15.3%) patients, respectively, can be additionally detected.

The worst SBP, HR, RR, SpO₂, and Temp were significantly different between the case and control (all $p < 0.001$), and there were also significant differences in Δ SBP ($p = 0.001$), Δ HR, Δ RR, and Δ SpO₂ ($p < 0.001$), but not in Δ Temp ($p = 0.739$). Multivariate logistic regression analysis based on a combination of the worst and Δ value continued to show significance in SBP, HR, RR ($p < 0.001$), and Δ RR ($p = 0.008$). The AUC of this model was 0.925 [0.872 – 0.978].

Conclusion: We concluded that changes in vital signs may help predict adverse events in hospital wards. Nevertheless, further research is needed to investigate how to apply this method in clinical practice.

Keywords: In-hospital cardiac arrest, rapid response systems, vital signs, delta values, adverse events, clinical deterioration

1. References

1. Andersen LW, Holmberg MJ, Berg KM, Donnino MW, Granfeldt A. In-Hospital Cardiac Arrest: A Review. *JAMA* 2019;321(12):1200-1210. DOI: 10.1001/jama.2019.1696.
2. Penketh J, Nolan JP. In-hospital cardiac arrest: the state of the art. *Crit Care* 2022;26(1):376. DOI: 10.1186/s13054-022-04247-y.
3. Ohbe H, Tagami T, Uda K, Matsui H, Yasunaga H. Incidence and outcomes of in-hospital cardiac arrest in Japan 2011-2017: a nationwide inpatient database study. *J Intensive Care* 2022;10(1):10. DOI: 10.1186/s40560-022-00601-y.
4. Hillman K. et al.; MERIT study investigators. Introduction of the medical emergency team (MET) system: a cluster-randomised controlled trial. *Lancet* 2005;365(9477):2091-2097. DOI: 10.1016/s0140-6736(05)66733-5.
5. Galhotra S, DeVita MA, Simmons RL, Dew MA, Members of the Medical Emergency Response Improvement Team C. Mature rapid response system and potentially avoidable cardiopulmonary arrests in hospital. *Qual Saf Health Care* 2007;16(4):260-5. DOI: 10.1136/qshc.2007.022210.
6. Andersen LW, Kim WY, Chase M, et al. The prevalence and significance of abnormal vital signs prior to in-hospital cardiac arrest. *Resuscitation* 2016;98:112-7. DOI: 10.1016/j.resuscitation.2015.08.016.
7. MD B, E J, PR B, SA B, BP W, J A. Recognising clinical instability in hospital patients before cardiac arrest or unplanned admission to intensive care. A pilot study in a tertiary-care hospital. *Med J Aust* 1999;171(1):22-5. DOI: 10.5694/j.1326-5377.1999.tb123492.x.
8. Schein RM, Hazday N, Pena M, Ruben BH, Sprung CL. Clinical antecedents to in-hospital cardiopulmonary arrest. *Chest* 1990;98(6):1388-92. DOI: 10.1378/chest.98.6.1388.
9. Franklin C, Mathew J. Developing strategies to prevent inhospital cardiac arrest: Analyzing responses of physicians and nurses in the hours before the event.pdf. *Crit Care* 1994;22(2):244-247.
10. Jones DA, DeVita MA, Bellomo R. Rapid-Response Teams. *N Engl J Med* 2011;365(2):139-46. DOI: 10.1056/NEJMra0910926.
11. DeVita MA. Use of medical emergency team responses to reduce hospital cardiopulmonary arrests. *Quality and Safety in Health Care* 2004;13(4):251-254. DOI: 10.1136/qshc.2003.006585.
12. Maharaj R, Raffaele I, Wendon J. Rapid response systems: a systematic review and meta-analysis. *Crit Care* 2015;19(1):254. DOI: 10.1186/s13054-015-0973-y.
13. Jones D, Bellomo R, Bates S, et al. Long term effect of a medical emergency team on cardiac arrests in a teaching hospital. *Crit Care* 2005;9(6):R808-15. DOI: 10.1186/cc3906.
14. Devita MA, Bellomo R, Hillman K, et al. Findings of the first consensus conference on medical emergency teams. *Crit Care Med* 2006;34(9):2463-78. DOI: 10.1097/01.CCM.0000235743.38172.6E.
15. Escobar GJ, Liu VX, Schuler A, Lawson B, Greene JD, Kipnis P. Automated Identification of Adults at Risk for In-Hospital Clinical Deterioration. *N Engl J Med* 2020;383(20):1951-1960. DOI: 10.1056/NEJMsa2001090.
16. Churpek MM, Edelson DP. Moving Beyond Single-Parameter Early Warning Scores

- for Rapid Response System Activation. *Crit Care Med* 2016;44(12):2283-2285. DOI: 10.1097/CCM.0000000000002105.
17. Churpek MM, Yuen TC, Edelson DP. Risk stratification of hospitalized patients on the wards. *Chest* 2013;143(6):1758-1765. DOI: 10.1378/chest.12-1605.
18. Gerry S, Birks J, Bonnici T, Watkinson PJ, Kirtley S, Collins GS. Early warning scores for detecting deterioration in adult hospital patients: a systematic review protocol. *BMJ Open* 2017;7(12):e019268. DOI: 10.1136/bmjopen-2017-019268.
19. Lee A, Bishop G, Hillman KM, Daffurn K. The Medical Emergency Team. *Anaesth Intens Care* 1995;23:2:183-186.
20. Smith GB, Prytherch DR, Jarvis S. A Comparison of the Ability of the Physiologic Components of Medical Emergency Team Criteria and the U.K. National Early Warning Score to Discriminate Patients at Risk of a Range of Adverse Clinical Outcomes. *Crit Care Med* 2016;44:12:2171-2181. DOI: 10.1097/CCM.0000000000002000.
21. Gardner-Thorpe J, Love N, Wrightson J, Walsh S, Keeling N. The value of Modified Early Warning Score (MEWS) in surgical in-patients: a prospective observational study. *Ann R Coll Surg Engl* 2006;88(6):571-5. DOI: 10.1308/003588406X130615.
22. Bartkowiak B, Snyder AM, Benjamin A, et al. Validating the Electronic Cardiac Arrest Risk Triage (eCART) Score for Risk Stratification of Surgical Inpatients in the Postoperative Setting: Retrospective Cohort Study. *Ann Surg* 2019;269(6):1059-1063. DOI: 10.1097/SLA.0000000000002665.
23. Churpek MM, Yuen TC, Winslow C, Meltzer DO, Kattan MW, Edelson DP. Multicenter Comparison of Machine Learning Methods and Conventional Regression for Predicting Clinical Deterioration on the Wards. *Crit Care Med* 2016;44(2):368-74. DOI: 10.1097/CCM.0000000000001571.
24. Lee YJ, Cho KJ, Kwon O, et al. A multicentre validation study of the deep learning-based early warning score for predicting in-hospital cardiac arrest in patients admitted to general wards. *Resuscitation* 2021;163:78-85. DOI: 10.1016/j.resuscitation.2021.04.013.
25. Kia A, Timsina P, Joshi HN, et al. MEWS++: Enhancing the Prediction of Clinical Deterioration in Admitted Patients through a Machine Learning Model. *J Clin Med* 2020;9(2). DOI: 10.3390/jcm9020343.
26. Churpek MM, Adhikari R, Edelson DP. The value of vital sign trends for detecting clinical deterioration on the wards. *Resuscitation* 2016;102:1-5. DOI: 10.1016/j.resuscitation.2016.02.005.
27. J Kellett, A Murray, S Woodworth, Huang W. Trends in weighted vital signs and the clinical course of 44,531 acutely ill medical patients while in hospital. *Acute Medicine* 2015;14(1):3-9.
28. St. Marianna University Hospital, webpage. "The activation criteria of Rapid Response Systems." (https://www.marianna-u.ac.jp/hospital/outpatient/team/team_02.html).
29. Kanda Y. Investigation of the freely available easy-to-use software 'EZR' for medical statistics. *Bone Marrow Transplant* 2013;48(3):452-8. DOI: 10.1038/bmt.2012.244.
30. Naito T, Fujiwara S, Kawasaki T, et al. First report based on the online registry of a Japanese multicenter rapid response system: a descriptive study of 35 institutions in Japan. *Acute Med Surg* 2020;7(1):e454. DOI: 10.1002/ams2.454.