Predictors of 30-day readmission based on machine learning in patients with heart failure: an essential assessment for precision care

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INVITED COMMENTARY

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Despite the availability of device therapy and pharmacological interventions, many patients with heart failure (HF) are suffering from exacerbation and poor prognosis.1 Multiple factors can contribute to a constant decline in heart and physical function, as well as psychological problems in patients with HF, resulting in repeated hospitalization and decreased quality of life.2 Readmission is a characteristic of patients with HF, which can lead to adverse outcomes and financial burden of patients.3 Therefore, it is crucial to identify significant predictors for readmission among this population so as to take some valid and target management measures to reduce readmission and enhance post-discharge care.

Yu and Son4 published an article in the European Journal of Cardiovascular Nursing on a systematic review that identified significant predictors and synthesized manageable risk factors of 30-day readmission in patients with HF. In that paper, they used the evidence-based procedure to search all the articles about HF, machine learning (ML), risk factors, and prediction models published between May 2013 and April 2023. Thirteen articles were included in their review, with eight studies using a retrospective design and five using a prospective study design. The authors extracted data on 30-day readmission reasons and readmission rates, ML performance, and significant predictors of the risk of 30-day HF readmission. Finally, 60 significant predictors and nine categories were found in this study.

The strength of that review is that it is the first systematic review of ML-based 30-day readmission prediction model in patients with HF. Over the last decade, research and development of AI-based technologies in healthcare have increased, showing great potential to support patients, clinicians, and healthcare infrastructure.5 Compared to conventional statistics, which is often used on small sample sizes and in studies with short periods of follow-up, the advantages of ML are obvious. It can treat complex and multi-dimensional data, and deal with non-linear correlations and unstructured interaction. This helps clinicians to identify all the risk factors as precise as possible. Machine learning is considered as the future for chronic disease management (such as predicting patients’ clinical outcomes or contributing the precision care) since it can screen a multitude of factors from big data, and help nurses capturing complex risk factors and individualized needs of patients. Although the predictive performance of prediction models included in the review ranged from poor to excellent (area under the receiver operating characteristic curve ranging from 0.51 to 0.93), it does not mean that ML is not better than traditional statistics. The advantage of ML treating big data cannot be ignored, as it offers opportunities to improve the quality of patient-centred care and readmission prevention practices.6,7

What has this study added to our knowledge of 30-day readmission in patients with heart failure?

Sixty significant predictors of 30-day readmission and nine categories were found in this study. This is important information for nurses to take some targeted and valid management. However, as we know, the weight of each factor contributing to an event is inconsistent in the process. Yu and Son’s review only showed predictors of readmission but did not show the weight of each factor. Hence, it remains unknown what factors are most important and to which nurses need to pay more attention. Therefore, studies are required to show meta-analytic results to demonstrate which factors have higher weights over each other.

What will the results help us to enhance the quality of care and develop an individual strategy?

Due to the huge economic burden of HF, clinicians have been looking for disease management programmes to reduce cost, readmission
rates, and improve the quality of life of patients. These programmes usually involve multidisciplinary approaches and result in significant expenditures. Nurse-led disease management interventions have been found to be cost-effective in heart failure management. The findings of the present study can enable nurses to fully understand the individual characteristics of patients, and provides information on individual needs of patients. This information assists in determining more precise intervention targets for preventing unplanned HF readmission.

**What are the avenues for research?**

Since we do not have hard evidence on the relative importance of ML techniques over traditional statistics, future meta-analyses should look into the question which statistical approaches are better. Further, the role of patient-reported outcomes (PROs), when analysed with ML techniques, remains untapped. Indeed, a good management strategy requires the active participation of patients and patients’ perspective ought to be included. For instance, ML can be used to assess the impact of disease and treatment on symptom burden and health-related quality of life from the patient’s perspective. Combining disease-specific factors and PROs can serve as a valuable foundation for shared medical decision-making between clinicians and patients. However in Yu and Son’s review, the risk factors identified were limited to clinical characteristics. Hence, more research is required to collect and integrate all types of data, such as clinical data, administrative data, and PROs, to identify all the predictors of readmission. Doing so, the accuracy of the prediction models can be improved.

**Conflict of interest:** none declared.

**Data availability**

No new data were generated or analysed in support of this research.

**References**