MEDINFO 2023 — The Future Is Accessible
J. Bichel-Findlay et al. (Eds.)

doi:10.3233/SHTI231078

Continuous Remote Patient Monitoring for Post-Discharge Heart Failure Management: Workflow Modeling Using Discrete Event Simulation

Rema PADMAN[a,1], Anirudh Vaidhyaa VENKATASUBRAMANIAN[a], Wei Ning CHI[b], Anthony SOLOMONIDES[b], Nirav SHAH[b]
[a]*Carnegie Mellon University, Pittsburgh, USA*
[b] *NorthShore University HealthSystem, Chicago, USA*

Abstract. The Cascade-HF protocol is a Continuous Remote Patient Monitoring (CRPM) study at a major health system in the United States to reduce Heart Failure (HF)-related hospitalizations and readmissions using wearable biosensors to collect physiological data over a 30-day period to determine decompensation risk among HF patients. The alerts produced, coupled with electronic patient-reported outcomes, are utilized daily by the home health team, and escalated to the heart failure team as needed, for proactive actions. Limited research has examined anticipating the implementation and workflow challenges of such complex CRPM studies such as resource planning and staffing decisions that leverage the recorded data to drive clinical preparedness and operational efficiency. This preliminary analysis applies discrete event simulation modeling to the Cascade-HF protocol using pilot data from a soft launch to assess workload of the clinical team, evaluate escalation patterns and provide decision support recommendations to enable scale-up for all post-discharge patients.

Keywords. Heart failure readmission, continuous remote patient monitoring, discrete event simulation, workflow modeling and analysis

1. Introduction

An estimated 6.5 million adults live with heart failure (HF) in the United States (US) and more than 64 million people worldwide [1], with medical costs and readmissions placing an increasingly heavy burden on health systems everywhere. Recent efforts to mitigate this challenge have integrated remote patient monitoring (RPM) as an essential aspect of patient management, with non-invasive RPM devices reporting success in improving patients' quality of life and reducing readmissions [1]. Continuous remote patient monitoring (CRPM) systems combine a spectrum of physiological measurements to accurately capture patient status and alert the care delivery team for appropriate interventions to avoid rehospitalizations [2]. However, a serious challenge that may inhibit the success of CRPM implementations is the limited ability to robustly estimate workload of the care team and consequently make appropriate staffing decisions. In this study, we build on a pilot CRPM deployment at a major health system in the US, called

[1] Corresponding Author: Rema Padman, email: rpadman@cmu.edu.

Cascade-HF [2], by leveraging discrete event simulation (DES) techniques to mirror the real-world execution of CRPM in a virtual environment to estimate the care team's workload and its variability. We also evaluate escalation patterns in the post-discharge period for patients at varying levels of readmission risk at discharge. This approach and the associated platform may facilitate an improved understanding of operational challenges for the health system regarding workflow and operational decisions before scaling up the deployment for all post-discharge patients.

2. Methods

Discrete event simulation (DES) has been widely applied to investigate workflow modeling challenges in healthcare and minimize disruptions during complex deployments [3]. DES approach enables us to mimic the behavior and performance of actual decision-making settings and processes using mathematical models, anticipate the potential consequences and evaluate intervention designs as simulated scenarios. Abstract simulation designs must be instantiated with representative real-world data to estimate parameters such as readmission risk at discharge, likelihood of adverse events, such as Atrial Fibrillation in HF patients, and activity times of the clinical team during their follow-up engagement with patients. This study designs and implements a preliminary DES model that incorporates these requirements to ensure its real-world usability and generalizability to complex health conditions beyond heart failure.

2.1 Design Components of the Simulation Model

The preliminary simulation model builds on the HHN workflow displayed in Figure 1 [2]. This protocol is initiated for a patient based on the readmission risk score generated at discharge [4]. It then follows patients for 30 days post-discharge, tracking various physiological alerts produced by an analytics platform that collects data from a wearable biosensor worn by patients from the time of discharge [2]. Emphasis is given to the multivariate change index (MCI) alert that applies a personalized physiologic baseline established in the first 48 hours by studying the user's respiration, heart rate, sleep, and other parameters [2]. Other physiological alerts such as Atrial Fibrillation, Tachypnea, Tachycardia, Bradycardia, and weight changes provide additional risk pathways for the patient. Daily patient-reported outcomes (ePROs), such as the incidence of shortness of breath, chest pain, etc., are also included to evaluate patient health status. Clinicians' responses to these alerts follow an escalating cascade from the HHN team to cardiology specialists, with increased diuretic dosage in response to increased risk or weight gain, and closer monitoring of patients. This is performed dynamically, based on patient status, and may be sustained or de-escalated based on improvements or escalated to hospital readmission.

2.2 Calculating Patient's Readmission Risk at Discharge

The Clinical Analytics Prediction Engine (CAPE) consolidates a varied spectrum of clinical and diagnostic metrics and applies logistic regression, adjusted for multi-collinearity, to estimate readmission risk and identify relevant predictor variables [4]. We use the estimated risk scores to categorize patients into three distinct levels - High, Medium, and Low, shown in Table 1, to simulate workload variability and staff allocation and evaluate its sufficiency to address patient requirements at each risk level.

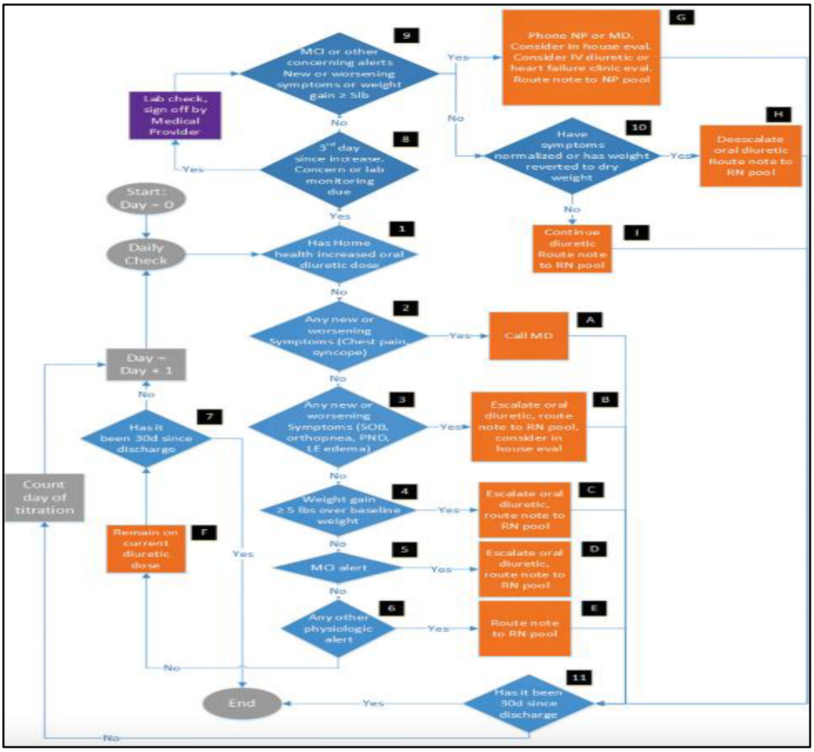

Figure 1. Home Health Nurse (HHN) workflow [2]

Table 1. Risk Categorization and Composition.

Risk Category	Risk Criterion	Patient Composition
Low	<=75th percentile	28%
Medium	> 75th and <=90th percentile	32%
High	> 90th percentile	40%

Table 2. Simulation Model Parameters.

Alert/Activity Type	Distribution Type
Nurse Consultations	Normal
MCI Alert	Lognormal

2.3 Data and Distributions used to Instantiate the Model

Our primary data source is a wearable biosensor, *VitalPatch* (VitalConnect, California), worn by patients for 30 days post-discharge and is collected and organized by the *pinpointIQ* platform (physIQ, Illinois). The CRPM solution thus combines a clinical-grade sensor that collects near real-time, continuous, ambulatory vitals with cloud-based analysis that applies clinical rules and machine learning models [2]. We instantiate the model using data from a pilot deployment with forty-four patients between 2019 – 2021 to identify patient composition within each risk level (Table 1) and estimate the likelihood and frequency of alerts for each level. Clinical guidance determined activity times of the home health team for key activities in the workflow model.

2.4 Implementation of the DES model

The model was implemented in Arena simulation software (Rockwell Automation, Wisconsin, student version 16.1) and designed to execute over a 30-day period for a cohort of 25 patients. Table 2 displays the distributions fitted to crucial model parameters. Red Zone (chest pain, syncope) and Yellow Zone (shortness of breath, orthopnea) escalations were also used to model exogenous conditions in the simulation and were randomized for each patient, conditional on the original CAPE score.

3. Results

3.1 Simulated Patient Summary and Generation of Alerts

The composition of patients of different risk levels mirrored the empirical composition observed from the pilot study (Table 1). Simulated patients are of age between 40 and 85 years and weigh between 100 and 250 pounds. An initial titration dose of diuretic between 40mg to 80mg was set for the patients, based on their CAPE scores.

Over the 30-day period, the 25 simulated patients generated four occurrences of red zone escalations for high-risk patients who then exit the model due to readmission (Table 3). Yellow zone escalations and MCI-based alerts result in increased diuretic titration and transition to the escalated pathway that maintains the new diuretic regimen until symptoms disappear. Out of ten patients who transitioned to the escalated care pathway, four witnessed a further deterioration in health and exited the model for readmission.

Table 3. Alert Summary.

Alert Type	Frequency	Additional Time Spent/Patient to Address Alerts
Red Zone	4 patients	7 minutes
Yellow Zone	6 patients	15 minutes
MCI	4 patients	11 minutes
Escalation Pathway	10 patients	8 minutes

3.2 Estimating the Workload of the Home Health Nurses

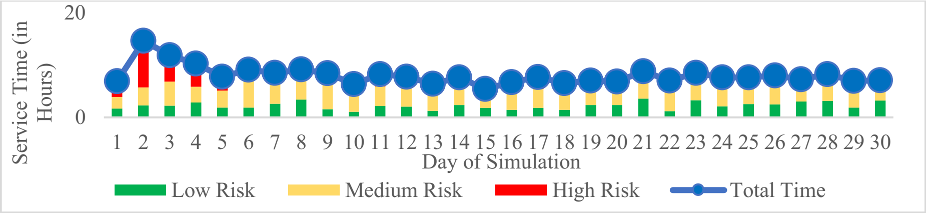

Figure 2. Service times by risk level & variability in home health nurses' workload.

Figure 2 displays the result of monitoring 25 simulated CRPM patients at the same time. We observe that the first week post-discharge is crucial and a significant determining factor of the care team's workload, after which the workload for the home health team stabilizes. The total service time, depicted on the Y-axis of Figure 2, can be used to plan optimal staffing levels by week. A similar pattern is seen with 5 simulated patients, but with a reduced total service time. As the patient load varies, the simulation model can be executed to re-estimate workload and associated changes in staffing requirements.

4. Discussion

This study presents some capabilities of a discrete event simulation model in robustly determining key operational efficiency issues with CRPM deployments, such as workload of the HHN team. This model design is scalable to new alert categories and risk pathways. It is also generalizable and can be quickly adapted to other therapeutic areas that currently suffer from increased rates of readmissions and are leveraging the use of remote patient monitoring to improve care quality and reduce risk of hospitalization. However, there are a few limitations with the approach presented here. The real-world usability of simulation is largely determined by the size and detail of the data sample used to instantiate the model. This study used a limited sample that may constrain applicability of the model's insights. Future work will use data from a larger cohort of patients to instantiate and validate the model. Ongoing extensions will also test the design of prediction models embedded in the DES model using the new daily information, such as alerts, diuretic escalation, and physiological changes to generate a dynamic readmission risk score for early and more targeted interventions.

5. Conclusions

This paper presents a scalable and generalizable approach using CRPM and DES that (a) home healthcare teams and operational decision makers of health systems can use to dynamically estimate staffing requirements and determine appropriate interventions that enable efficient care utilization, (b) nurses/clinicians can use to anticipate and improve preparedness in the context of HF-related readmissions, and (c) researchers can leverage to generate new hypotheses on alert mechanisms, risk prediction indices and design of efficient post-discharge care pathways to potentially reduce risk of readmissions.

Acknowledgment

We are grateful to M. Shanker, M. Nakhate, C. Paraschiv, U. Ravichandran, Y. Zhu, K. Larimer, and the Rice Foundation for their support during the development of this study.

References

[1] Olivari Z, Giacomelli S, Gubian L, Mancin S, Visentin E, Di Francesco V, Iliceto S, Penzo M, Zanocco A, Marcon C, Anselmi M. The effectiveness of remote monitoring of elderly patients after hospitalisation for heart failure: the renewing health European project. Int J Cardiol. 2018;257:137-42.

[2] Chi WN, Reamer C, Gordon R, Sarswat N, Gupta C, White VanGompel E, Dayiantis J, Morton-Jost M, Ravichandran U, Larimer K, Victorson D, Erwin J, Halasyamani L, Solomonides A, Padman R, Shah NS. Continuous Remote Patient Monitoring: Evaluation of the Heart Failure Cascade Soft Launch. Appl Clin Inform. 2021 Oct;12(5):1161-73, doi: 10.1055/s-0041-1740480.

[3] Zhang X. Application of DES in health care: a systematic rev. BMC Health Serv Res. 2018;18(1):687.

[4] Shah N, Konchak C, Chertok D, Au L, Kozlov A, Ravichandran U, McNulty P, Liao L, Steele K, Kharasch M, Boyle C. Clinical Analytics Prediction Engine (CAPE): Development, electronic health record integration and prospective validation of hospital mortality, 180-day mortality and 30-day readmission risk prediction models. PLoS One. 2020 Aug 27;15(8):e0238065.