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Dynamic Optimization of Caregiver Schedules Based on Vital Sign Streams

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ABSTRACT

Hospital facilities use a collection of heterogeneous devices, produced by many different vendors, to monitor the state of patient vital signs. The limited interoperability of current devices makes it difficult to synthesize multivariate monitoring data into a unified array of real-time information regarding the patients state. Without an infrastructure for the integrated evaluation, display, and storage of vital sign data, one cannot adequately ensure that the assignment of caregivers to patients reflects the relative urgency of patient needs. This is an especially serious issue in critical care units (CCUs). We present a formal mathematical model of an operational critical care unit, together with metrics for evaluating the systematic impact of caregiver scheduling decisions on patient care. The model is rich enough to capture the essential features of device and patient diversity, and so enables us to test the hypothesis that integration of vital sign data could realistically yield a significant positive impact on the efficacy of critical care delivery outcome. To test the hypothesis, we employ the model within a computer simulation. The simulation enables us to compare the current scheduling processes in widespread use within CCUs, against a new scheduling algorithm that makes use of an integrated array of patient information collected by an (anticipated) vital sign data integration infrastructure. The simulation study provides clear evidence that such an infrastructure reduces risk to patients and lowers operational costs, and in so doing reveals the inherent costs of medical device non-interoperability.

Keywords: Critical Care; Nurse Scheduling; Optimization

1. Introduction

Preventable, in-hospital medical errors account for between 100,000 and 200,000 deaths in the United States each year [1]. There have been many attempts to determine the underlying causes, including the reports of Health Grades, a leading healthcare ratings organization [2], and the Joint Commission, a non-profit organization seeking to improve safety through healthcare accreditations. A recent Joint Commission report, for example, investigates incidents of deaths and serious injuries related to long-term ventilation [3]. Of the incidents reviewed, approximately 20% - 35% were found to be associated with insufficient staffing levels and/or a delayed response to an alarm; none were related to ventilator malfunction.

The extent to which we can mitigate patient risks caused by delayed responses and insufficient staffing, rests on addressing the problem of effective caregiver scheduling. Notable prior work, including that of McManus *et al.* [4] and Zai *et al.* [5] has used queuing theory to model the operation of existing healthcare facilities and admission procedures. The existing practices of "manpower allocation" in respiratory care is considered by Matthews *et al.* in their 2006 study [6], while Gajc *et al.* examine the effects of having 24-hour (mandatory) versus on-demand critical care specialists on staff. All of these studies begin with data from existing facilities and analyze the data to build a model and determine how the model responds to various stresses. In contrast, other researchers (e.g. Gallivan *et al.* [7] and Shahani *et al.* [8]) look to improve workflow and decision making processes by mining data from existing CCUs. Indeed, the general problem of designing nurse scheduling algorithms has received considerable attention, including hierarchical [9], greedy [10], genetic, and simulate annealing approaches [11]. Here we connect the important problem of nurse scheduling to the practical implications of device heterogeneity and non-interoperability.

models of alarm sequences, generated by mining real historical data from vital sign streams.

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