An Alert Notification Subsystem for AI Based Clinical Decision Support: A Protoype in NICU

Catherine Inibhunu, MIEEE
Ontario Tech University
Oshawa, Ontario, Canada

Carolyn McGregor AM, SMIEE
Ontario Tech University
Oshawa, Ontario Canada
University of Technology Sydney
Ultimo, NSW, Australia
ORCID: 0000-0002-0491-4403

J. Edward V. Pugh, MBBS, FRCPC
McMaster Children's Hospital
Hamilton, Ontario Canada
Faculty of Health Sciences,
McMaster University
Hamilton, Ontario Canada
Faculty of Health Sciences,
Ontario Tech University,
Oshawa, Ontario Canada

***Abstract*—The potential for recommendation systems integrated within clinical workflows for effective dissemination of vital information needed in decision making at the bedside is explored in this paper. Our premise is that by utilizing big data analytics platforms for processing high frequency physiological data from multiple patients, fused with clinical context, we can generate recommendations on patients detected as potential for onset of conditions, and that if such information is communicated on time to the appropriate health care providers could have an impact when making decisions on care of critically ill patients. To support this, we have designed and developed an alert notification subsystem that combines vast analytics to detect abnormal patient's physiology, determine who is on service at the bedside and then generate appropriate notification to that care provider during their schedule time in a hospital critical care unit.**

Keywords—Recommender Systems, Health Recommender Systems, Alert Systems, Big Data Analytics, Intelligent Notification, Knowledge Systems.

I. INTRODUCTION

Clinical decision support systems driven by artificial intelligence (AI) hold great promise to improve healthcare, through improved outcomes for patients and resource efficiencies. However, the limited adoption of AI in healthcare to date demonstrate that there are barriers to deployment and translational impact. A key component of responsible deployment in order to close the loop from research to application through deployment is understanding the best approach to integrate the intervention with the care teams' workflow. That integration should be driven by how and to whom the alert notification should be provided to [1] [2].

Alert notification systems have parallels with recommender systems. Recommender systems are defined as tools and techniques developed for helping a user make a decision when buying items in e-commerce [3]. In the era of big data, recommender systems continue to play a significant role in filtering information using techniques in data mining and pattern recognition to generate useful information for users. There are three main filtering techniques suggested in the literature that are utilized in recommender systems [4]. These include; collaborative filtering that is based on collecting and composing knowledge from users input such as in e-commerce, content-based filtration based on aggregation of knowledge about users and descriptions in historical data, and hybrid filtering noted as a combination of content-based and collaborative filtering [3].

Depending on the domain and filtering techniques, the main aspect of recommender systems is noted as the ability to present personalized options mainly in e-commerce platforms such as Amazon [3]. For recommender systems to provide the recommendations needed in critical decisions, they need to be equipped with knowledge. AI is at the heart of knowledge generation in recommender systems. AI algorithms may use either supervised or non-supervised methods in knowledge creation for which, recommendation systems generate personalized recommendations. A central challenge on these techniques is the quality of features in generating recommendations particularly what information is gathered to make a meaningful recommendation [3]. For recommendations systems in e-commerce, the targeted notification recipient is the consumer for which the recommendations are personalized and the deployment is through advertising space on websites or targeted emails and SMS texts. However, in healthcare, the targeted recipient is complicated by rotating shift work resulting in changes to the care team composition.

In healthcare, with vast volumes of data collected in clinical databases and electronic health records representing patient health status such as diagnosis, treatment, laboratory results and administered drugs, lies the potential for recommender systems to use all available data to generate meaningful patient centered recommendations. Such recommendations can be utilized for making informed decisions about patient care. Recommender systems in healthcare are referred to as health recommender systems (HRS) [5] and can also be said to be knowledge or intelligent systems. There are two types of recommendations in HRS, those that are centered on a patient as the user (PU) or those that are centered on healthcare providers as users (HPU). Patients can benefit from HRS that supports them to view or act upon medical information and at the same time enables them to make informed decisions about their health [6]. Healthcare providers can benefit from recommendations generated from HRS especially since they are faced with an information overload and a challenge to distinguish which could be helpful. This is especially challenging when faced with a critically ill patient and/or preterm infant in intensive care where quick decisions are to be made on the appropriate care of that patient. HRS geared towards HPU are said to increase data usability by reducing information overload thus optimizing decision making on many aspects of healthcare delivery [4]. Within this paper we focus on HRS geared towards recommendation for healthcare providers and within the case study context of neonatal intensive care.

HRS that effectively process continuous high frequency data streams from bedside monitors and sensors from critically ill patients especially those in critical care units is an open research area [7] [8].

Content based filtration techniques that can be utilized to aggregate vast data can also be applied in HRS. Specifically, content based algorithms can be developed utilizing high frequency patient data as well as additional contextual information from electronic health care records. All this information represents patient health status such as diagnosis, treatment, laboratory results and administered drugs to generate recommendations to assist in narrowing differential diagnosis options that could be utilized in critical decision scenarios such as the care of a preterm infant receiving care in a neonatal intensive care unit (NICU).

Currently health recommender systems use static data to generate recommendations [9]. They are further challenged by the method by which they send notifications regarding the alert and are usually limited to bedside or nursing control station alerting. The dynamic nature of data streams and healthcare urgency warrants a different approach to generating recommendations at the right time, to the right people and systems, within the right context and content especially in a NICU.

Methods to enable the integration of these HRS within the care team's workflow as noted earlier, are yet to be explored and would enable communication of the right information to the right people and systems at the right time. Solutions to date have been limited to univariant, i.e. single data stream, audible threshold alarms that lead to alarm fatigue [10]. Most health care teams have moved beyond pagers to communication about patient state via SMS texts and email. Thus, systemic approaches to enable HRS to notify the care team via SMS texts and email is required. Scheduling systems contain information about the health care team composition at any given time and hence the integration of HRS with scheduling systems is required.

In this paper we address the following open research areas; (i) a framework and system for health care recommendation using real-time algorithms that analyze high frequency patient data streams captured from monitors and sensors, (ii) augmentation of that data with clinical input to generate informed notifications(alerts) for health care providers, and (iii) quantified and optimized alerts to reduce any alarm fatigue at the same time providing insightful and effective information that can allow healthcare providers in intensive care and specifically for our case study, NICU, to plan appropriate treatment actions for a preterm infant in NICU.

To address these open areas, we have designed and developed an alert notification subsystem that (a) conducts a null hypothesis statistical test to quantify the predictive values from analytical algorithms that utilize patient physiology such as heart rate and respiratory rate to identify patients who have breached some predefined thresholds (b) determine who is on service and should therefore be aware of that breach by querying a clinical scheduling system and (c) then generating an optimized notification message (alert) that is communicated to healthcare providers on service using email and Short Messaging Service (SMS) services.

This processing involves extending (a) the framework for big data AI based real-time clinical decision support which can be provisioned externally to an organization as Health Analytics as a Service [7] and (b) instantiation of those extensions within the Artemis cloud platform [8]. These extensions enable integration with off the shelf rostering systems to facilitate notification of alters to the right person at the right time using appropriate communication technologies.

The rest of the paper is organized as follows; section II highlights related works, section III details the extended framework, section IV details the extended platform, section V details a clinical case study and section VI concludes the paper with highlights on future works.

II. RELATED WORKS

There are various areas of healthcare where HRS have been proposed. Of relevance to this research are approaches that use patient data to generate recommendations that can be utilized by healthcare providers as they consider potential differential diagnoses and make critical decisions about patient care.

Using data from a patient population diagnosed with diabetes and heart insufficiency researchers in [9] proposed a system that recommends the best possible therapy as well as expected therapy time by predicting outcomes generated using interpretable neural networks that doctors can use during treatment decisions. The researchers claim that their work can contribute to simplification of administrative functions boosting quality of patient management. The researchers utilize static datasets and focus on the models accuracy on predictions. High frequency physiological and/or other sensors data streams are not incorporated within that research.

Within intensive care units (ICU), researchers in [11] recognize the need for recommender systems in predicting and classifying health state of critically ill patients with an aim of reducing mortality rate. Their work uses content-based recommendation technique to develop a classification model to observe ICU patients and used IBM cloud to store the patient's data. However, their method did not work with any real time patient data and relied on the cloud system for data storage only.

In recognition that high performance computing was necessary for intelligent systems in health care, a big data framework known as Artemis for knowledge discovery fusing high speed physiological data captured from bedside monitors in neonatal intensive care units (NICU) was introduced in [12]. The instantiation of that work within a Big Data and AI based platform has spanned multiple research studies and demonstrated in quantifying physiology such as heart rate and respiratory rate with variability thresholds that may detect patients with potential onset infection of neonatal sepsis [13] [14].

Even though all these research studies highlight the potential for models to be utilized in vast sectors in clinical care, it is not clear how these can be integrated in real clinical settings to be utilized effectively by healthcare providers as they care for patients in NICU. As noted in [5] HRS have become essential tools in decision-making processes in the healthcare sector especially in ensuring valuable information is available at the right time, as such research remains in transitioning recommendations into clinical practice in order to close the loop from research to application.

To address these challenges, the contributions in this research seeks to tackle the open areas outlined in section 1 by expanding on the work that has been completed in McGregor et al. [12] and in so doing, we combine principles in content based recommendations to generate data-driven alerts within a big data computing platform complemented with a communication engine, integrated with an off the shelf hospital rostering system that sends a notification to the appropriate healthcare providers on service when an alert is generated. A null hypothesis statistical test is integrated within the review of proposed alerting algorithm rules to ensure that only relevant notifications are generated and communicated ensuring no alarm fatigue on healthcare providers. The developed prototype is instantiated within an NICU case study to extend the current Artemis deployment within the NICU at McMaster Children's Hospital, Ontario Canada [7] [8].

III. Extended Framework

In this section, we present first an overview of the existing big data framework that was introduced to address data processing challenges from high frequency data streams captured from multiple devices and sensors monitoring patients in NICUs. As noted in [15] the potential to utilize this data for complex analytics is not possible in the current hospital settings and was characterized as a big data problem.

The Artemis Framework was introduced and the developed platform was prototyped in multiple hospitals for real time analytics [7] [8] as well as retrospective clinical case studies such as, neonatal sepsis detection [13] [16], temporal analysis of physiological data streams [15], temporal patient state quantification [14] and classification of spells [17].

Figure 1 outlines the framework for big data AI based real-time clinical decision support which can be provisioned externally to the organization as Health Analytics as a Service. The architecture contains 7 components as follows.

a) Data Collection: Mulitple medical devices within critical care are connected to patients using sensors that gather data about the patients state of health. These devices transform body signals into high frequency data streams that are usually displayed on monitors at the bedside. Artemis Cloud has functions that connects to existing medical devices to acquire the data for further processing.

b) Data Acquisition: Acquisition of high frequency data within Artemis Cloud is a seamless process with minimal impact on current process flow at the bedside. High frequency data is viewed at the bedside monitors and simultaneously streamed to Artemis.

c) Data Buffering and Transmission: The process of data acquisition is performed by data buffering and transmission software whose function is to transmit data onto the Adaptive API of Artemis Cloud and to buffer the

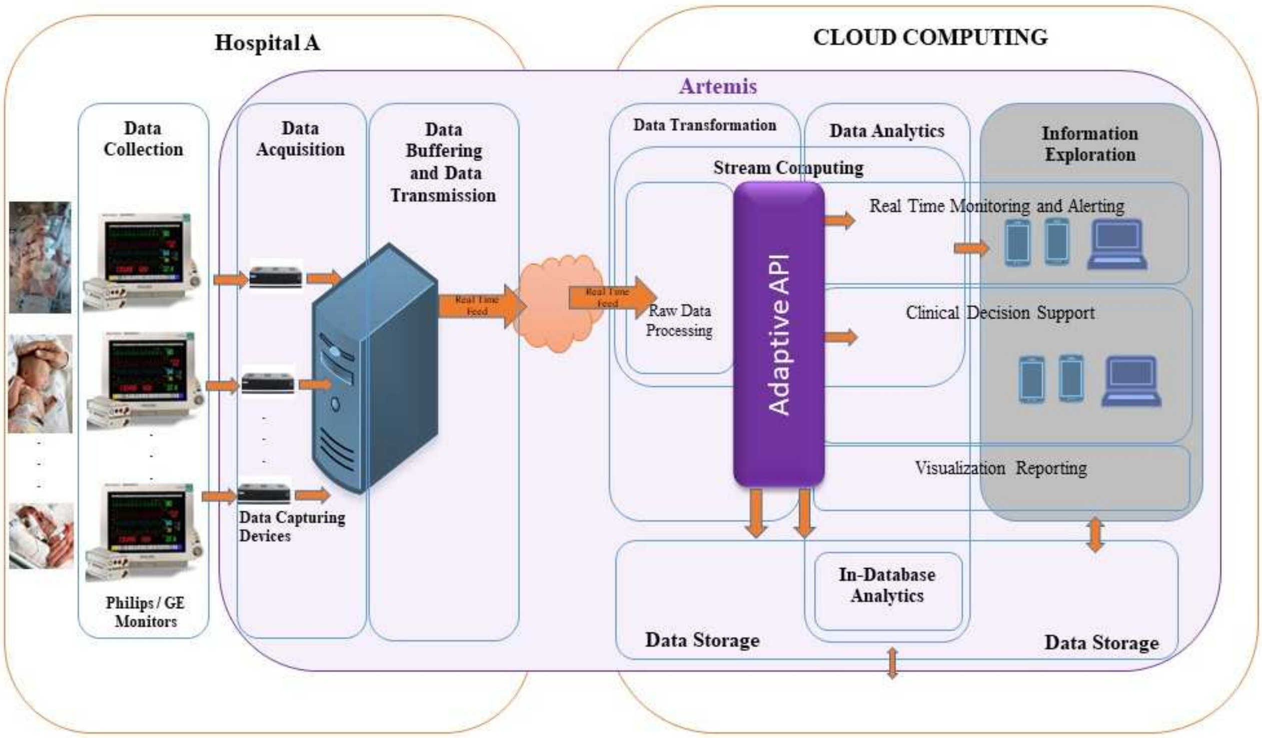

Figure 1: Big Data and AI Based Health Analytics as a Service Framework [7]

data when transmission functions are not available due to outages on the network or the Adaptive API.

d) Data Transformation: This component supports multiple data ingestion and transformation workflows which prepare and transform data for consumption by other services such as analytical algorithms or storage.

e) Data Analytics: This component enables several data analytics modules to be deployed, and these modules can consume the data made available by the data transformation component. This enables prompt temporal abstractions and analytics to be generated that can reflect information about the state of a patient from the perception of a range of medical conditions.

f) Data Storage: All data flowing within Artemis Cloud is stored using functions in this component. This includes the raw data, the temporal abstraction and resulting analytics. The storage of raw data enables retrospective data analysis as well as clinical case studies.

g) Information Exploration/Visualization: This component within Artemis Cloud enables information exploration and visualization thus presenting actionable information to users.

Extensions of the data capture and processing components within Artemis was demonstrated in [8]. The researchers developed an adaptive API that allowed ingestion of multiple data streams out of bedside monitors and standardized within a middleware and then distributed as a service for vast analytical services to consume.

This approach demonstrated the ability for multiple applications to process the same data streams using multiple algorithms. As shown in Figure 2, the API generates processed data streams as topics that can be subscribed to within the vast analytical modules. This design allowed the same data to be processed by the multiple algorithms that can be integrated within Artemis. Such a method guarantee uniformity in all the data processed across many analytics algorithms.

Within this paper we extend the Artemis Framework to

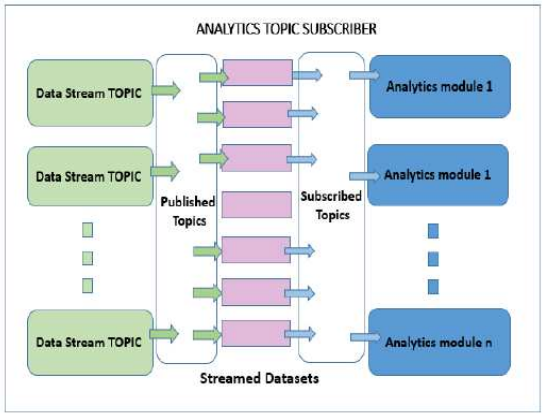

Figure 2: Real-Time Streaming API [7]

include the integration of the Scheduling System to facilitate proactive notification to those who are on service and responsible for that bed space. The extended Artemis framework is presented in Figure 3. This extension introduces the hospital's Scheduling System and extends the functionality of the Real-Time Monitoring and Alerting Component. The details of this extension are outlined next.

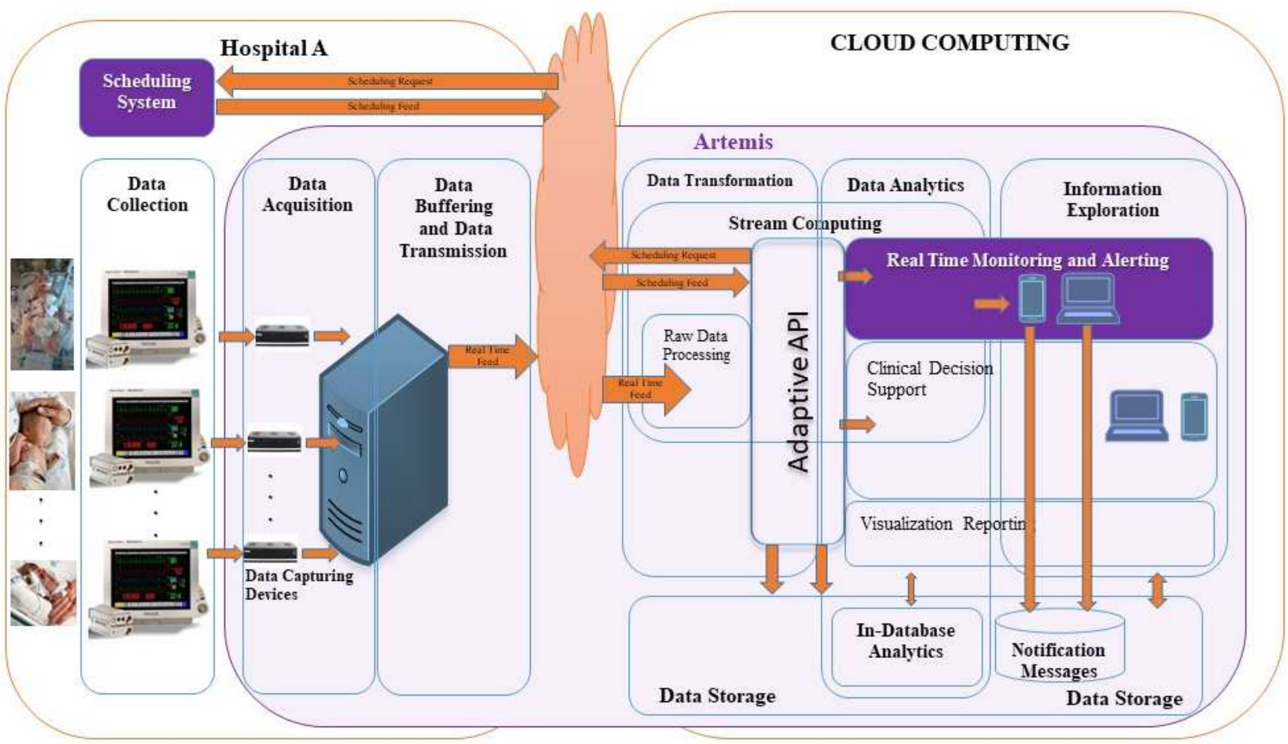

Figure 3: Extended Big Data and AI Based Health Analytics as a Service Framework to incorporate Notifications and integration with Scheduling System

Real-time Monitoring and Alerting: This component is extended with two modules.

Alert Generation: This module consists of functions that utilize existing or new analytical algorithms that continuously monitor and detect the health state of a patient and then determines if a predefined threshold is breached or concerning patient state is reached. If a breach is reached, then an alert is generated that details the patient health state during the breach.

Alert notification: This module receives the alert generated from the alert generation module and determines who is on service from a hospital scheduling system, and responsible for that bedspace, and therefore should be notified with the alert. Notification messages are then created and sent to appropriate health care providers and simultaneously recoded in the database for further analysis.

Within the existing Real-Time Monitoring and Alerting component of Artemis as described in [8], instantiation of these components involves development of a robust communication subsystem that seamlessly integrates with existing Artemis architecture. To facilitate this process we have designed and developed an Alert Notification Subsystem within the Real-Time Monitoring and Alerting component of the Artemis platform described next.

IV. Extended Platform

The current Artemis Cloud platform implementation enables high frequency data streams captured from bedside monitors and processed in the adaptive API for real time analysis [8].

Extension of this platform to allow alert notifications involves the design and development of an alert notification subsystem. We describe the process flow and technologies that have been utilized in this development.

A. Proposed Alert Notification Sub-System

The notification sub-system has been created using InfoSphere Streams and a combination of Stream Processing Language (SPL), C++, Java and Python programming languages. InfoSphere streams performs the real-time analytics and generates the alerts that are to be processed by the Alert Notification Sub-system. The alert notification subsystem has been created using C++, Python and Java programming languages. As per the framework components, the proposed Alert Notification Subsystem contains two key components namely an Alert Generator and Notification components. The message process flow between the two components is described next with a pictorial view in Figure 4.

1) Alert Generator Component and Associated Submodules

First is the Alert Generator Component (AGC) whose main functions are to utilize the algorithms deployed as part of the analytical modules within the adaptive API of Artemis [8] as well as any clinical context to determine patients that have potential for the condition or patient state of interest. This information is utilized by the AGC to generate an alert. The alert is generated and sent to the Notification Component whose main function is to send notifications by email and by SMS to appropriate teams.

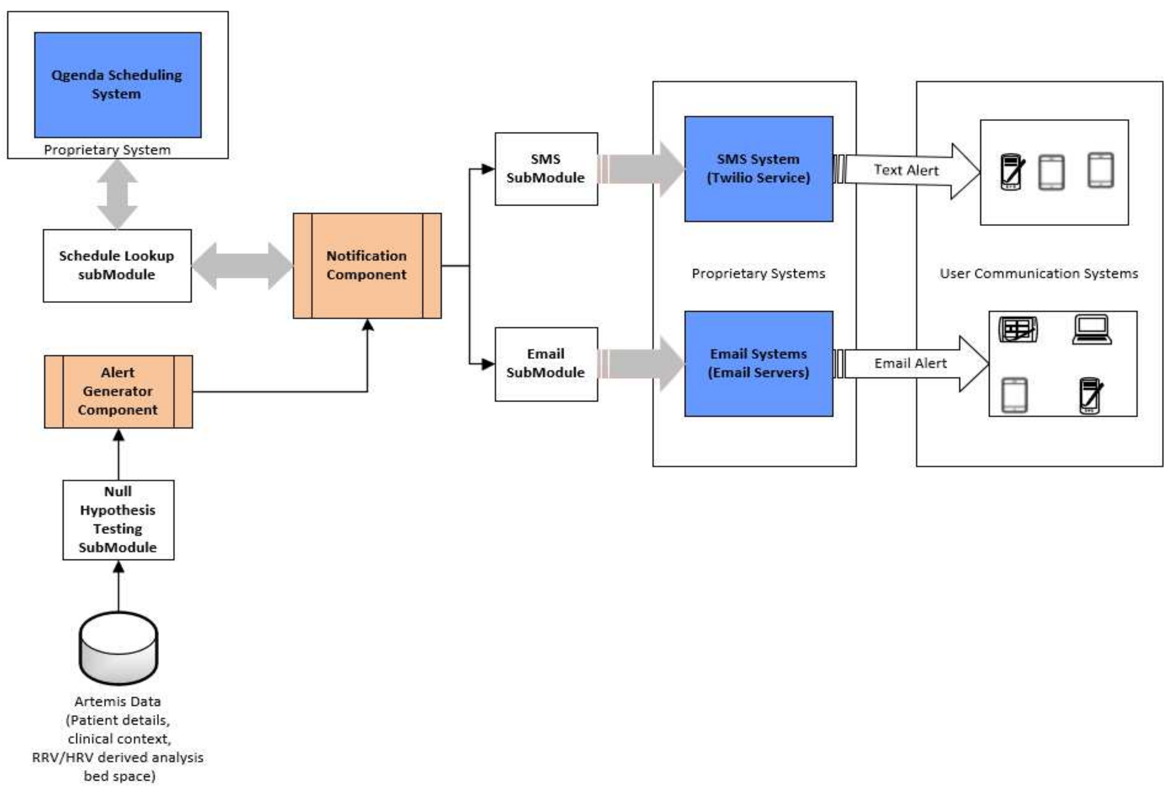

Figure 4: Message Process Flow in the Alert Notification Subsystem

2) Notification Component and Associated SubModules

This module consists of several components as follows; to send out a notification, first the Notification component needs to determine who is on service at the NICU and responsible for that bedspace to be notified about the status of the patients with the alert. It is important to note here that several roles have different responsibilities for the same bed space necessitating multiple people to be notified. This component sends a message to the Scheduling System lookup submodule that contains scheduling details in a hospital [18]. Information about staff is retrieved from the Scheduling System, specifically their role name, the email and phone numbers of on duty staff at that particular time. This lookup ensures that only information of the staff on duty during when an alert is generated are retrieved from the scheduling system. Of note to detail here is that the fields to extract were determined as part of a privacy impact assessment process (PIA) as required in Ontario, Canada. The name, of those on staff at any time in the NICU is publicly available and hence name as well as role could be extracted within this case study.

Upon retrieving the list of staff on schedule, the notification component sends messages to both the SMS submodule as well as the Email submodules to send the notification to each staff on duty. We note that privacy by design principles outlined in [19] are adopted to ensure that none of the private information of staff (email, phone numbers) retrieved from the scheduling system are retained in the developed notification subsystem.

In this research we have used a proprietary software (Twilio messaging system) [20] to send SMS messages. For prototyping purposes, we are utilizing the university email server to send the emails. A clinical case study applying the proposed subsystem is detailed next.

V. CASE STUDY

McMaster Children's hospital is located in Hamilton, Ontario, Canada. The NICU at McMaster Children's hospital provides specialized care for premature and ill term infants along with infants who have a variety of health conditions that require intensive care [21]. The NICU provides Level 3 nursery and highest level of care. Artemis was installed previously within the Level 3 and Delivery Suite bed spaces for a total of 51 bed spaces and its reliability and availability has been previously reported in [7].

As noted in section II, Artemis is a big data and AI based platform to support clinical decision support. It represents an instantiation of the related big data and AI based framework for clinical decision support. As part of the Artemis commercialization project, various algorithms were integrated as consumers of the data processing within the API. Two particular algorithms were designed in quantifying heart rate and respiratory rate of a preterm infant to detect the potential for late neonatal sepsis (LONs) [13]. Late Onset Neonatal Sepsis (LONS) is a serious and potentially fatal medical condition when an infant has a blood stream or cerebrospinal fluid (CSF) bacterial infection that has started beyond 72 hours of life [22].

Early diagnosis of sepsis is of ultimate importance for the patient's outcome [13] [16]. Prior LONS algorithms used heart rate variability (HRV) only derived from heart rate [23] in attempts to create mechanisms for earlier diagnosis of LONS and as a result have a significant issue with false positives as well as false negatives [23] . This false positive issue is because there are other causes of reduced heart rate variability than LONS. HRV and respiratory rate variability (RRV) concurrently adds value to HRV analysis by distinguishing between patients with low HRV due to imminent sepsis and those patients with low HRV due to the presence of confounding factors such as surgery and narcotics [13]. The researchers noted that the potential application of monitoring HRV in neonatal infants arises from the observation that abnormal HRV could be associated with neonatal mortality and long term illness. As such, there is potential for HRV and RRV to provide non-invasive diagnostic tool for clinically important neonatal conditions [13]. HRV/RRV Algorithms are some of the analytical consumers of the adaptive API developed in [8]

The basis of the HRV /RRV algorithms provides a solid path in addressing the open research areas outlined in the introduction. We argue that it is possible to develop a health care recommender system by (a) building real-time algorithms such as the HRV and RRV that detects abnormal patterns in patient physiology and (b) when the outputs from those algorithms are augmented within clinical context, it is possible to generated informed notifications (alerts) that can be communicated to the appropriated health care providers and (c) that those alerts can be quantified and optimized to reduce any alarm fatigue at the same time providing insightful and effective information that can allow healthcare providers in NICU to plan appropriate treatment actions for a preterm infant in NICU.

Performing a clinical research study using Artemis within the NICU, McMaster Children's Hospital of this instantiation required ethics approval which was sought for and approval was received for the data collection study from the Hamilton Health Sciences REB (HiREB 2859-D) and Ontario Tech University (#14736). On clinical case study, approval was received for the LONS study from the Hamilton Health Sciences REB (HiREB 4833-C) and Ontario Tech University (#15536).

A. Use Case Scenario

The following is a hypothetical scenario to demonstrate how an alert may be communicated to NICU staff, a pictorial flow is presented in Figure 5.

Its 8:30AM on a weekend day. The Artemis alert generator component has detected abnormal HRV/RRV thresholds on five different NICU patients based on continuous temporal analysis of multiple patients' physiology and clinical context. These assessments are performed hourly hence the possibility of the detection of five at the same time. An alert is then generated and the process flow on how many emails and SMS messages that are to be sent is presented in Figure 5.

From the Alert Notification Subsystem, the schedule lookup submodule has extracted the following staff descriptions on those who are on service {ATT: Attending physician, PFs: Program fellows, CFs: Clinical fellows, NPs: Nurse practitioners, and PAs: Physician assistants}.

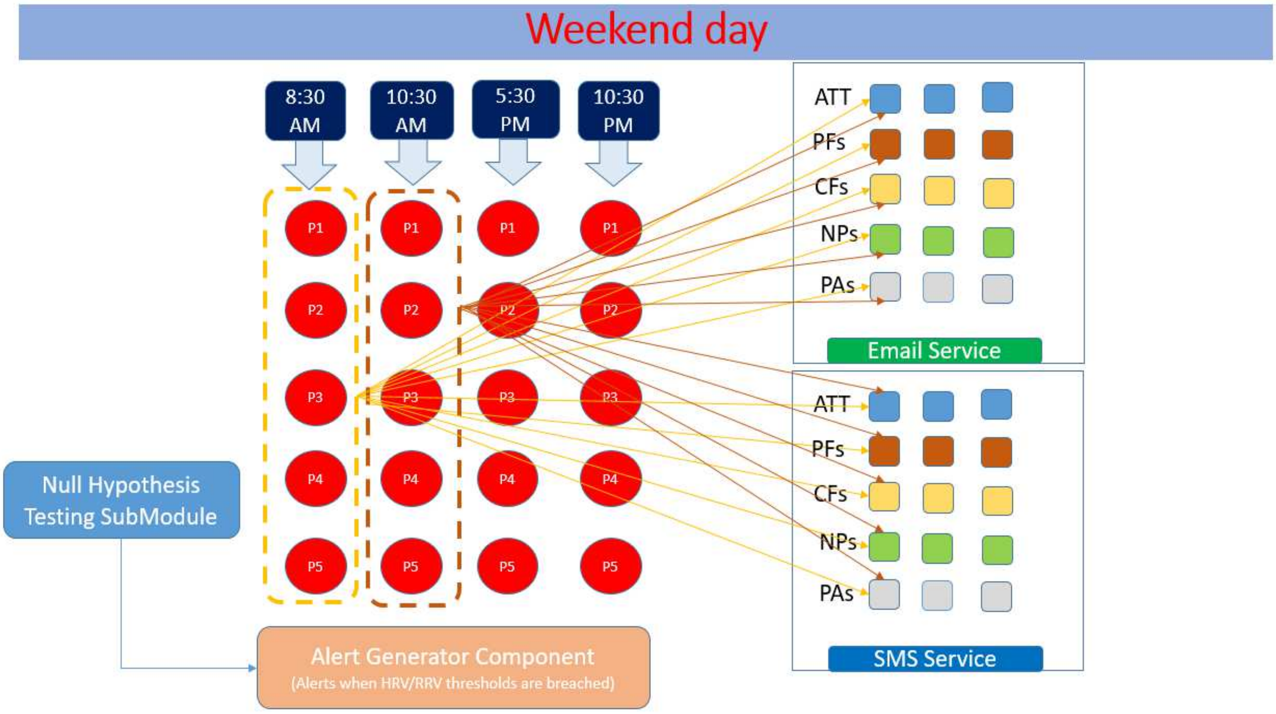

Figure 5: Alert Notification in a Weekend Day

An alert on patients (p1 to p5) will be communicated to the ATT, PFs, CFs, NPs and PAs and on duty at 8:30 in the weekend day morning. Therefore, each of the staff with these roles will receive one email and one text message with details on the 5 patients with their alert descriptions. If after 2 hours, the same 5 patients are detected to go over the HRV/RRV thresholds, alerts are generated and notifications sent to the same staff on duty.

VI. Conclusions and Future Works

In this paper we recognize the potential for recommender systems in clinical care. This is particularly important if recommendations are relayed back on time to healthcare providers as they make critical decisions on best care for patients in NICU. This paper has presented extensions to a Big Data, AI based framework for health analytics as a service that integrates with the hospital's scheduling system and enables alerting via SMS texting and email to those who are on shift at the time of the alert who are caring for that patient. These extension components were added to the Artemis platform that is an instantiation of the Big Data, AI based framework for health analytics as a service.

To facilitate this process, this research has presented an Alert Notification Subsystem instantiated as a pilot product within Artemis platform. This process allows alerts to be generated based on analytics on patient physiology and clinical context, then determining who is on service when the alert is generated and then sending a notification to that staff by email and SMS notifying them of the patient that is detected as potential for LONs. Future publications will outline the clinical case study outcomes for the assessment of the integration of this LONS alert within clinical practice in the McMaster NICU as part of the next stage of user testing, clinical verification, validation and deployment.

As proposed in [1] [2] as part of a strategy for deploying responsibly, we have completed a 'silent mode' assessment that was performed at the same time as the availability assessment in [6] where the predictions are calculated in real-time and exposed to a group of clinical experts retrospectively but not acted upon in real-time. The outcome of this silent mode test is the subject of another publication that will be available in the future.

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