DOI: 10.1561/9781638282372.ch17

Chapter 17

Introduction to Section IV: Supporting Workflows and Making Workflow Insightful

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17.1 Introduction

This section on use cases in technology brings you to artificial intelligence, decision support, and three different examples of making workflow and care pathways insightful. From aspects of analysis in radiology to helping caregivers and management see how workflow in acute and hyper-acute care is actually going will be described. Making what we think is 'good' even 'better' requires detailed and accurate information and a sound understanding of what the information (may) mean.

The BigMedilytics (BML) project focused on bringing technology into use. This section offers a series of two settings and four different projects, with divergent points of focus and models. Each chapter brings its own insights and learning.

17.1.1 A Technical Description of Real-Time Location Technology (RTLS)

Many, many processes, care pathways, analysis, and diagnostic and therapeutic care in healthcare in general consist of a series of steps. Most of these are serial in nature, but parallel activities may occur. While these steps are often detailed in procedural documents, and some even include timelines, understanding efficiency, effectivity, and movements in caregivers and patients is difficult.

Where healthcare has learned from flight procedures to strengthen safety, we can also learn from logistically focused businesses on process management. An example of this could be the ‘just in time’ (Toyota motor corporation and its concept of Lean management). However, logistics involves physical motion, and much of healthcare is content driven, with very little outward motion to be detected.

In this chapter (Chapter 18: Real-Time Location System), an evidence-based solution is described. Wearing badges and labeling assets and patients with InfraRed (IR) and Radio-Frequency (RF) technology is combined making it safe for the high-technology density in healthcare. Importantly, the coding of tags and badges can be carefully configured to meet the privacy needs of individual, group, or cohort levels, thus dealing with potential concerns.

As you will see in this chapter and those following (Chapter 20: Innovative Use of Technology for Acute Care Pathway Monitoring and Improvements, Chapter 21: Monitoring Sepsis Patients in the Emergency Department, and Chapter 22: Technological Support for Paramedical Asset Management in a Hospital Setting), careful design is a key to success. Wireless technology makes the system easy to install and remove, as well as allowing it to be moved to other locations as needs occur.

We note as a point of general interest that the RTLS system used in BML allows for coding levels for badges, but is not suitable for data mining based on roosters (i.e., to assess whether an individual badge wearer is serially present and whether this is a confounder in the pathway.

17.2 Using Artificial Intelligence and Decision Support to Buttress Assessment of CT Scans of the Lungs

The amount of information is exploding, but our capabilities to search, assess, and use the stockpile have not improved proportionally. In a recognizable user case, the assessment and reading of CT scans in pulmonary disease were used to analyze its effect on accuracy, put-through time, and professional confidence in junior and senior radiologists (Chapter 19: Implementation and Impact of AI for the Interpretation of Lung Diseases in Chest CTs).

The expert system (Contextflow GmbH) was integrated into the hospital ICT system. When a radiologist had labeled an area of interest in a pulmonary CT investigation, the expert system would look for similar effects, search for descriptions and differential diagnostic options, and offer them to the radiologist for consideration in their specific case. This is all within seconds.

In a neatly worked out prospective study in both junior and senior staff radiologists (as both usability and needs might be influenced by experience on the job), Roehrich and coworkers show that it is safe and effective, as well as acceptable to the professional. They recognize in the lessons learned that cooperative efforts with the IT department and careful management of the use of AI and decision support must be monitored and coached. The 'right answer' remains that determined by the professional – the expert system offers input to be weighed and considered. Important in their study is that not only was put-through time analyzed, but they also looked at the professional aspects.

As using Big Data starts to be integrated into healthcare, this study allows generalizable insights into careful and safe integration. How often are we not aware of how 'the machine' is supporting us?

17.3 RTLS in Hyper-acute Care in the Emergency Department for Patients Suspected of Stroke

In this chapter, Paulussen and coworkers (Chapter 20: Innovative Use of Technology for Acute Care Pathway Monitoring and Improvements) describe a multidisciplinary, multi-location study into a mature time-sensitive workflow. They set out to assess whether this workflow: with only limited physical movement by the patient, but very time and content sensitive: can be analyzed using RTLS with the incorporation of selected data from the Electronic Medical Record (EMR).

Ischemic stroke requires rapid recognition, presentation in an Emergency Department (ED), diagnostics, and potential treatment. Stroke is an important cause of morbidity, chronic decrease in quality of life, and healthcare costs. The Elisabeth-TweeSteden Hospital is strongly organized, formally worked out an 12-step workflow, and offers both intravenous thrombolysis and intra-arterial thrombectomy on a 24/7 basis – therapy to be started within an hour of arrival in the ED.

Paulussen and colleagues use this mature system to assess the RTLS and query whether the use of the EMR time stamps is valid. They use RTLS and EMR data to search for potentially unknown bottlenecks in the workflow.

They argue and show data that EMR timestamps are non-valid and may even be confusing; that with cooperation by healthcare professionals – who need to be aware of how RTLS works, wear badges, and potentially adapt the positioning of the patient – RTLS can be very valuable. Their numbers suggest that the neurology workflow is far faster and the spread is far smaller than that department thought based on EMR data. They also show that analysis of EMR data requires deep mining as well as a user-based understanding of what is done with EMR timestamps.

This study also mentions (see also Chapter 4: Lessons Learned in the Application of the General Data Protection Regulation to the BigMedilytics Project) that while regulations may focus on the protection of the patient and their data, less work has – as yet – been done on the privacy aspects for the professional. Their study stayed well away from individual professional monitoring and focused on cumulative (group fidelity) data. With more than 4.5 million RTLS data points and a large number of EMR items, it is almost self-evident that a Big Data approach is needed.

They were able to find, discuss, and implement remediation as well as analyze the effects of this remediation. The reader should be able to translate their study and its environs to situations and locations they might be interested in.

17.4 RTLS in the Emergency Department for Patients Suspected of Being Septic

In this chapter (Chapter 21: Monitoring Sepsis Patients in the Emergency Department), Redon and coworkers, working in the Incliva Hospital Emergency Department, describe their use of RTLS in patients suspected of being septic. Their focus is on time-to-treatment in their high-volume, physically large ED.

Using a null measurement with retrospective EMR data to understand what the patient journey might look like, they carefully designed an RTLS environment within the ED to capture the important steps in the journey.

Using RTLS and adding selected EMR data points, they performed a prospective follow-up study to assess whether there was an overlap in the times found. As you might expect, they found strongly different times, with as an example a 1-hour time difference between the EMR time of departure compared to the RTLS data. This impacts the workload in the observation unit and may even delay or slow down earlier steps in the patient's journey, delaying treatment with antibiotics and potentially impacting morbidity and mortality. While not a focus in their study, Redon and colleagues report on how ill these patients were.

This group also advocates that the use of RTLS will allow analysis of outliers – in this case in times – and analysis of time spreads using the proprietary dashboard developed by Leitao and coworkers at Philips Research. Even the untrained eye can quickly assimilate information using this technique.

17.5 Finding Assets and to Use of RTLS to Support This

What is more frustrating than being in need of some medical device, be it a stethoscope or/and ECG kart, an anti-decubitus mattress, or something else? Looking where it should be all too often only increases the frustration.

Gutteling and Nelissen (Chapter 22: Technological Support for Paramedical Asset Management in a Hospital Setting), working at the OLVG in the Netherlands, describe an interesting alternative use for RTLS: a search and find tool. They use RTLS in a ward setting to label and monitor the location of a wide range of specific use and general use assets. They start by investigating how much time (nursing) staff need to find assets and using questionnaires how they feel about this. They even add a tool to the nursing Computer On Wheels (COW) and are disappointed when changes in logistics negate some of the expected effects.

In contrast to the other two chapters in this section which describe RTLS use, they use asset location as the principal input, instead of having the focus on patient and staff movement. They avoided the need for EMR data input and had little limitation from privacy aspects.

Using their study, they were able to produce data which suggest that using RTLS and by returning assets to predetermined location – but even if this later is not done – an institution may for the first time have actual insight into how many of a specific asset sort is needed to be able to always have one available, but without overinvesting in purchase and maintenance of assets. In other words, the dilemma of how many do we need to always have one available if we (really) need it, can be resolved using RTLS. They are even able to calculate potential savings.

Interestingly, they also suggest the generalization of use within healthcare and suggest that the department of medical technology might be a good choice as the 'owner' and facilitator of such a system, making it available to interested parties as needs and wants to arise.

17.6 What Reading It Can Bring You

This section describes two different applications of Big Data technologies within healthcare. First, artificial intelligence and decision support via an expert system (context flow) offer focused output from large databases, relevant decisions, and consideration, which can support a medical professional in weighing their perception for the most correct diagnosis or differential diagnosis. Second, real-time localization technology offers insights into a patient journey whether there are bottlenecks, and whether EMR data are in fact true. Tracking and facilitating medical assets and thus potentially reducing the bulk needed can also be done with RTLS.

The reader should have little difficulty – regardless of their work setting – in translating the information and models offered in this section to their own wants and needs. While not a focus, threads running through the chapter reinforce the need for multi-disciplinary approaches, a strong stakeholder, and careful preparation. Another thread the reader will pick up on is that despite RTLS being supportive technology, privacy, training, and careful monitoring require suitable attention.