12-12-2018

Improving time-critical, real-time, knowledge-based clinical decision support systems through usage data analytics

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Research-in-Progress

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Abstract

Knowledge-based decision support systems (KB-DSS) recommend decision actions based on stored knowledge. One of the challenges in time-critical clinical KB-DSS is the ability to maintain and continually improve the underlying knowledge-base. This challenge stems from the dynamic nature of the knowledge, and from the time constraints associated with the time critical interventions which do not afford for a traditional knowledge engineering approaches to feasibly occur during actual system usage. This paper explores the proposition that a usage-driven design approach could act as an enabler for the continual improvement of time critical, real-time KB DSS. We will describe a case study of an existing trauma reception and resuscitation time-critical real-time decision support system to express the challenges found in the current implementation and define the information requirements for supporting the proposed approach using a design-science-research methodology.

Keywords

Clinical Decision Support, Critical Care, Resuscitation, Injury, Trauma Reception and Resuscitation, Real Time, Usage Driven Design, Knowledge Based Decision Support Systems, Data Analytics

Introduction

Decision support systems (DSS) have much to offer towards managing healthcare costs and improving the quality of care by reducing clinical errors (Fichman et al. 2011; Kolodner et al. 2008; McDonald 1976). Over the years academic research have reported the use of computerized clinical decision support (CDS) systems to reduce clinical errors and improve the outcomes of medical interventions (Garg et al. 2005; Hunt et al. 1998; Kawamoto et al. 2005).

On the other hand, further studies into computerized clinical decision support systems have shown that errors can also be introduced by these systems (Ash et al. 2004; Ash et al. 2007a; Ash et al. 2007b; Brown et al. 2017; Mozaffar et al. 2017; Wright et al. 2017) . More than a decade ago, Weiner et al. (2007) coined the term "e-Iatrogenesis", which effectively means clinical errors caused by healthcare information systems arguing that the contemporary introduction of information technology into healthcare may result in harmful effects, and called for these effects to be "understood, measured and mitigated" (Weiner et al. 2007). In a contemporary setting, the introduction of electronic health record initiatives, the dissemination of technology, wearable IoT connected devices, and big-data initiatives into many aspects of healthcare (Bates et al. 2014) introduce additional complexity into health information systems. While this added complexity brings with it the increased potential benefits, it also introduces the potential for "e-Iatrogenesis".

As information systems are adopted and integrated into the workflow of the healthcare decision makers, the usage data collected along the way can be analyzed to provide insight. On the other hand, by not capturing this data, a lot of the information is lost. While the information can still be canvassed from the users of the system, it will always be second hand information. The adage "Those who do not listen to history are condemned to repeat it" (Santayana 1905) is very much applicable in this context. This insight gained from usage data can be used for many purposes. For example, it can be utilized as a learning or educational tool (Guerlain et al. 2005) or to review decisions of failed medical interventions (Calland et al. 2002) to determine the root causes of failure and learn from experience. This research, currently in progress, proposes that the insight derived from CDS usage data can be utilized to continually improve the associated decision support system itself by supporting the knowledge acquisition and discovery process, therefore mitigating the "e-iatrogenesis" phenomenon.

In the following section, prior works are reviewed and the gaps in research identified. Previous attempts of knowledge acquisition and discovery in the healthcare sector are presented. This research is positioned within these prior attempts and the contribution is identified. Secondly, a case study of an existing time-critical CDS is presented by identifying that without capturing *enough* information in usage data logs, gaining benefits through analytics and data science methods is not feasible. A set of brief requirements for capturing the usage information to support analytics is proposed. Thirdly, in the discussion section, a modified advisory system architecture is presented, and the benefits of such architecture are described and the challenges and aims of the current research in progress are presented.

Review of prior work

In this section prior works is reviewed to identify the research gap, therefore positioning this research in progress into the context of healthcare and knowledge-based decision support systems. Firstly, the need for continual improvement in healthcare CDS system is discussed. The need for additional information to support the continual improvement is also identified. Knowledge-based decision support systems are discussed, focusing on advisory and expert systems which are likely to be utilized in time-critical situations. Finally, the process of knowledge acquisition and knowledge discovery is also discussed.

Continuous vs Continual improvement

This paper uses the term "continual improvement" which, is defined here as improvement which happens often, and it is repeating. This definition is contrasted with the term "continuous improvement" which can be defined as improvement without pause or interruption. The latter is ideal to strive for, however in the healthcare domain, continual improvement is what is feasible and common practice.

The need for continual improvement in healthcare CDS systems

In the context of clinical decision support systems, Beeler et al. (2014) summarize previous identification of errors and makes recommendations to address these errors . Knowledge management of clinical decision support systems is identified as a novel and emerging field of research (Beeler et al. 2014). Wright et al. (2011), based on their study of internally-developed and vendor-based information systems, recommend to "Develop tools for ongoing monitoring of CDS interventions" to facilitate the incremental integration of the CDS with clinicians. Regular usage monitoring (for internally developed systems) should be part of governance practices - this approach would support a continual and incremental improvement of the CDS (Wright et al. 2011, pp. 191-192). Other independent research studies also identified a similar need for a *continual improvement* of CDS to better integrate the CDS to the workflow of physicians , and to better align the CDS to the evidence-based guidelines (Eppenga et al. 2011) which are regularly reviewed and changing through medical research and practice (Bates et al. 2003; Yoshida et al. 2018). Therefore, there is a need for a continual improvement of healthcare systems.

There is a reason why continual improvement of CDS systems remains an issue. In healthcare, the continual improvement of decision support systems (and information systems in general) face challenges that are unique – and some of these challenges have been identified by prior research. At individual level, the multidisciplinary setting in healthcare has different stakeholders with sometimes different interests and priorities. Often this means that a system has different classes of users using the same system in diverse ways depending on their profession (Venkatesh et al. 2011) or level of experience (Aron et al. 2011). Furthermore, the discretionary power of physicians to avoid or bypass systems also adds to the challenge as it is difficult to continually improve a system which is used in subversive manner – for example physicians delegating the use of IS to other healthcare workers to avoid using it (Kane and Labianca 2011). At team or group level, disagreements between different members can occur and some are based on clinical research findings, but others can be based on competing priorities of different stakeholders (Lee et al. 2013). This makes continual improvement of the system and its knowledge base challenging as the consultation of the different user groups is a lengthy and often challenging process - and consensus is difficult to achieve. In addition, the logistics of gathering information are complex, as shift work is a common practice (Lee et al. 2013, p. 132) and a challenge towards the research component of the knowledge-acquisition of a time-critical CDS (Lee et al. 2013, p. 132). The list of these challenges is not exhaustive but it's illustrative of some of the forces (Lewin 1946) that act against the continual improvement of healthcare CDS systems. To achieve the goal of continual improvement of time-critical CDS systems, additional measures are needed to counteract the abovementioned forces.

The need for continual improvement, coupled with the need for a more "objective" information about how time-critical CDS systems are used in practice constitute a gap which the current research in progress is focused upon. In the next section, knowledge-based expert and advisory systems architectures are presented based on prior research, to identify how their relevant architectures can be improved to support the continual improvement of the knowledge-base through usage data analytics.

Decision support systems - knowledge-based expert and advisory systems

Knowledge-based decision support systems suggest or recommend actions to the decision maker based on a knowledge base containing a representation of expert knowledge (Liang et al. 2005; Power 2008; Schuff et al. 2010; Turban 2011). Two types of knowledge-based systems are expert and advisory systems (Beemer and Gregg 2008; Liang et al. 2005, p. 566). Traditional expert systems are envisioned to solve a problem and deliver solutions to be chosen as decision options, whereas advisory systems guide the decision maker through the decision-making process by providing the relevant information (Beemer and Gregg 2008).

Both expert systems and advisory systems use a similar system architecture, which, at a high level, includes a knowledge-base, an inference engine and a user interface (Beemer and Gregg 2008). However, there are some crucial differences between the two. Expert systems are typically associated with a rules-based knowledge base and inference engine, whereby rules in algorithmic or logic forms are used to derive the system's recommendation. Advisory systems on the other hand are typically associated with a case-based reasoning approach. The latter approach works off the premise that a lot of expert decisions are based on heuristics and experience (Beemer and Gregg 2008). Figure 1 below illustrates the architectures for expert and advisory systems.

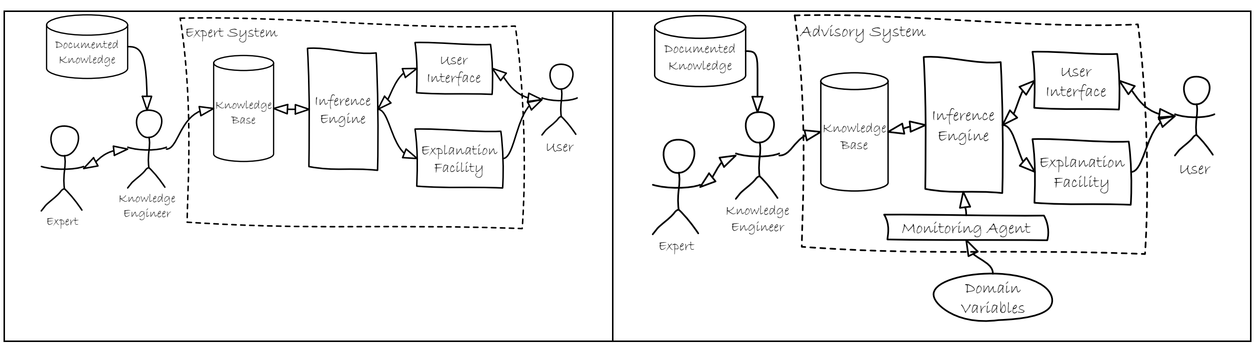

Figure 1: Advisory and Expert Systems architecture adapted from (Beemer and Gregg 2008; Liang et al. ; Turban 2011)

Both rules-based and case-based approaches have their strengths and limitations. The rules-based approach may not capture the full extent of the tacit knowledge of the experts, as this knowledge is thought to depend on heuristics and experience of the expert. On the other hand, the rules-based approach is easy to review and explain, which makes it suitable for domains where such scrutiny is required such as healthcare where the decision support needs to be evidence-based and aligned to agreed guidelines. The second "case-based-reasoning" approach is more iterative, and it may even build the knowledge base from the expert's tacit knowledge as it builds the memory of the different "cases" such as is the case with ripple-down rule approaches (Compton et al. 1992). Case base reasoning is suitable for complex decision-making tasks where the outcome is not known. This approach, however, may not always work and is dependent on the memory of the past decisions to drive the future decisions. Another challenge of the case-base reasoning is the difficulty in explaining its recommendations in some instances.

One of the challenges of these knowledge-based systems is the knowledge acquisition and discovery. In the architecture of expert and advisory systems shown in Figure 1, the knowledge acquisition is essentially an open-loop, whereby the knowledge-base is built from research activities and experts often with the help of a knowledge engineer. (Beemer and Gregg 2008; Liang et al. 2005). This architecture doesn't allow for self-learning of knowledge from the system usage patterns, and therefore this self-learning needs to be done through a consultative process. Turban (2011) has proposed an improved architecture by identifying an additional "Knowledge refinement" step within the inference engine as a new area of research. The "knowledge-refining system" can automatically adjust the knowledge-base from an evaluation of recent past performance, thus creating a small closed-loop system between the inference engine and the knowledge base (Turban 2011, pp. 550-552). However, the "knowledge refinement" step does not act as a trigger for improvements to the knowledge-base, but rather it functions to increase the accuracy of existing decisions, so, arguably, it cannot be classified as a knowledge acquisition or knowledge discovery.

This research proposes to close this loop by utilizing system usage logs combined with analytics methods to facilitate the knowledge acquisition and discovery. This information can also serve as a trigger for when additional knowledge engineering activities are required to update the knowledge base part of the knowledge acquisition. A prior approach for knowledge discovery is discussed in the next section.

Knowledge acquisition and knowledge discovery

Knowledge acquisition in the context of the Knowledge Management (and KB-DSS) is the process where knowledge is gathered from the experts and is codified into a knowledge base (Liang et al. 2005; Turban 2011, pp. 554-568). The process is usually facilitated by a knowledge engineer who is trained to understand and overcome the challenges of this activity – for example canvassing tacit knowledge from experts and codifying knowledge into a knowledge base (Turban 2011, p. 550).

In the context of this research, the question is "How can the system itself facilitate this process of continual improving the knowledge-base?" An attempt to answer this question is based on prior research in this field and the identification of any gaps.

A preliminary systematic literature review in the critical-care and emergency treatment area revealed that current CDS systems are based on the traditional expert system architecture, where there is no closed loop between usage and the knowledge acquisition.

After broadening the search to other systems in healthcare including non-time critical domains, it was found that a novel research by Larburu et al. (2017) demonstrated a system whereby the decision history captured by a CDSS is used to enhance the knowledge-base of a system through a knowledge discovery process. *Knowledge discovery* in this context is defined as a process that derives actionable knowledge and insights from raw data (Fayyad et al. 1996). Larburu et al. (2017)'s research utilized an existing system (DESIREE) – a breast-cancer treatment CDS. The DESIREE system showed that it is feasible to enhance the knowledge base of a CDS using decision history in a non-time-critical setting (Larburu et al. 2017; Muro et al. 2017). This research aims to extend that approach to apply to time-critical, real-time KB-DSS systems, and by examining the broader concept of usage which includes the decision history and other information.

Case Study – Trauma Reception and Resuscitation

A case study of the implementation of a trauma reception and resuscitation (TRR©) decision support system is presented. This real-time decision support system has been in operation at a major trauma center - The Alfred Hospital in Melbourne, Australia for more than a decade (Fitzgerald et al. 2006b). The TRR© system was implemented as a knowledge-based DSS, where the knowledge base contained a set of algorithms and rules compiled through consultation with a panel of experts and the relevant guidelines (e.g. ATLS). The inputs of the system consist of real-time data streams from various equipment, patient details and manually-entered treatments/procedures and diagnoses (Fitzgerald et al. 2011). The inference engine of this advisory system is algorithm-based and utilizes these inputs to produce visual prompts to assist the physicians with identifying the appropriate course of action for trauma resuscitations. The system also captures the diagnoses and treatments/procedures applied. At the end of the intervention, this information is printed and attached to the patient file.

Prior to its deployment, the TRR© system was initially evaluated using simulations involving experts. After the first phase, the system was evaluated using a randomized controlled interventional study over a period of two years (Fitzgerald et al. 2011; Fitzgerald et al. 2008; Fitzgerald et al. 2006a). The evaluation was done by panel of medical and nursing professionals utilizing captured video and data which included clinical parameters and other relevant information. The evaluation concluded that the TRR© system was effective and that it increased the percentage of error free resuscitations during the critical first 30 minutes and improved clinical outcomes (reduced morbidity) (Fitzgerald et al. 2011).

After deployment, the knowledge-base of the TRR© system was updated, with additional algorithms being added to their knowledge-base, with over 40 algorithms developed (Lee et al. 2013). The algorithms are inter-related and in a typical trauma situation multiple algorithm can run simultaneously (Lee et al. 2013). The algorithms were developed by expert physicians in consultation with healthcare nurses, utilizing research techniques described by Lee et al. (2013). The process of developing the algorithms is essentially a knowledge-acquisition process through which the knowledge base of the TRR© system was built.

Currently the TRR© system is going through a re-design to include the use of a google-glass wearable device which would input commands directly into the CDS and display critical alerts and vital signs (Chowdhury et al. 2017), so it presents an opportunity to utilize the usage data to support its knowledge acquisition. We shall, in the first instance identify a brief set of requirements for the capture of the information, set out in the table below.

Requirement	**Justification**
The data captured must be in a structured format.	While non-structured data can still be analyzed, most data science methods require data in a structured format.
The data captured must include the corresponding meta-data to aid analysis	The meta-data is required for the effective use of analytics.
The data should be compatible with standardized formats in healthcare systems	While this is not a hard-requirement, it will assist with integration and interpretation.
The data captured must be time-stamped with the time of occurrence	This will allow temporal analysis as well as correlations of temporal events. The temporal analysis will assist with determining the timeliness of the alerts.
Where possible the user's identification should be captured whenever a user inputs data	By capturing the user identification of the user, analysis can be done to identify usage issues at individual, group or organizational level.
The data captured by the CDS must include: • The information entered by the user to the CDS • The decisions made by the user • The outcome of the intervention and decision entered by the user • The recommendations provided by the system as CDS outputs • Version identifiers for all connected systems	This information will primarily allow the knowledge discovery and assist with the knowledge acquisition.

Table 1: Proposed information requirements to support knowledge discovery

A disadvantage of the current TRR© system is the inability to facilitate learning from the captured data (other than through consultation of the users involved in the intervention). While the current system was designed to capture the required data to evaluate the randomized controlled interventional study, in practice this information is printed and attached to a patient file, rather than stored in a database in a usable format for analytics (Fitzgerald et al. 2011). Additional analysis of the information captured revealed that while the information captured by the system supported the video-audit intervention that validated the system, it would not fully support contemporary analytics methods including unsupervised or supervised learning and other data science methods that can be utilized to gain insight from this data. A further challenge posed was the fact that the data was not persistently kept in a data store, but rather printed and added to the patient file. The requirements detailed in Table 1 above are a first step towards facilitating learning from the captured usage data.

Discussion

Figure 2 below shows the architecture of an advisory system (as previously discussed), annotated with the inputs and outputs that are utilized by the TRR system. The diagram also shows the proposed usage-driven knowledge discovery process which allows user-generated data to be captured and utilized by the knowledge-acquisition process.

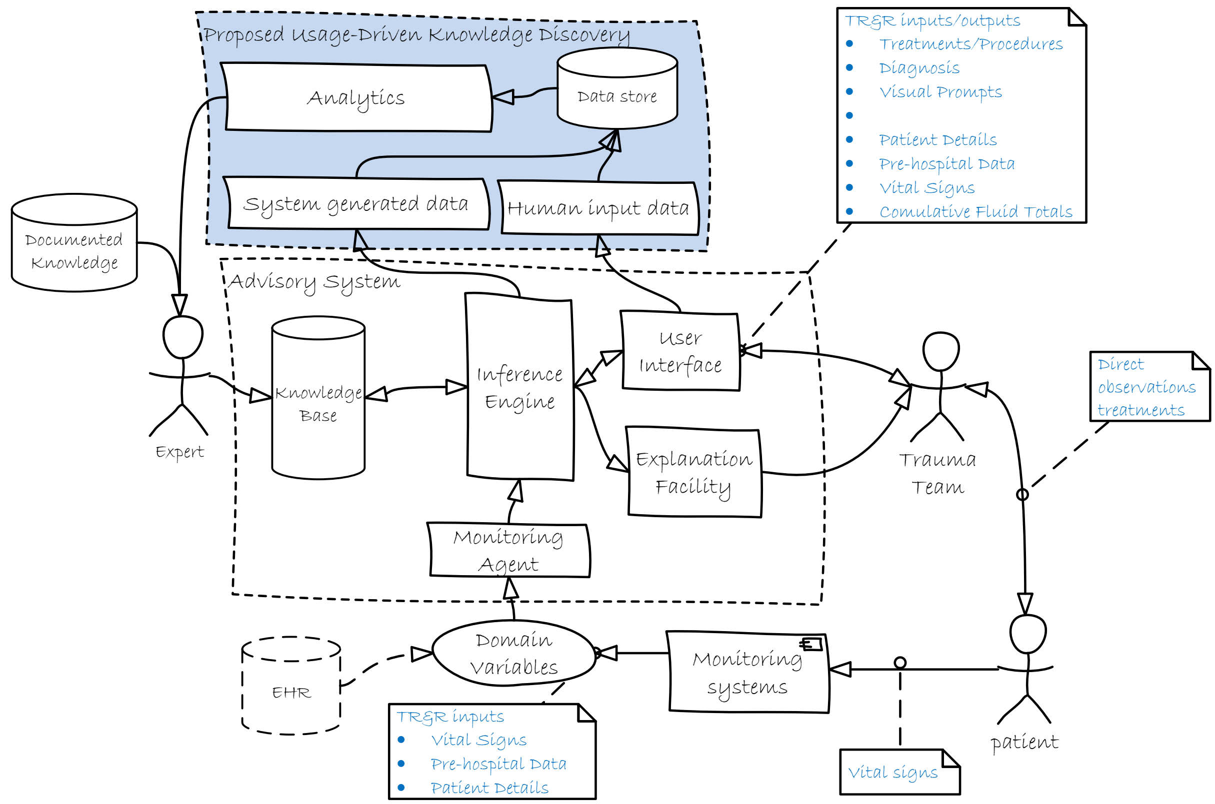

Figure 2: Proposed flow of the usage-driven design of an advisory system annotated with the information of the TRR© system (adapted from Beemer and Gregg (2008); Fitzgerald et al. (2008); Turban (2011))

This approach can help improve governance practices of CDS systems through improved system monitoring (Wright et al. 2011, pp. 191-192). For example, if a critical alert is regularly ignored by staff, there could be an indication that either the alert does not function as expected (generally according to the guidelines), or the decision maker (e.g. physician) made a deliberate decision contrary to that alert. This could have several implications. One possibility is that the physician(s) may have acted upon tacit knowledge which is not yet coded into the knowledge base. Another possibility is that the physician(s) may not have followed the guidelines due to some other reason such as technology aversion. These situations may require an intervention, either to fix the gap in the knowledge base, elicit knowledge from the user(s) or raise awareness to the benefits of the CDS and increase use. The insight resulting from the knowledge discovery would initially trigger the continual improvement initiative and then provide "objective" insight to the expert to assist the improvements to the knowledge base.

Before the abovementioned architecture can be realized, the advisory system needs to capture the relevant usage data. The data can be de-identified (to maintain the privacy of patients) and stored into a format which allows analytics and data science methods to be used on the data to derive insight. The methods used by the data science initiatives are multidisciplinary and include machine learning, statistical learning, pattern recognition etc.(Amirian et al. 2017). The focus of this research is to define a data model and explore the challenges of capturing and making the data available for use by these data science methods.

This research addresses a current design and research problem and creates an artefact (a data model and an associated architecture) and aims to also evaluate the artefact. Design science research is the most suited approach as a methodology to perform this type of research (Baskerville et al. 2018; Hevner and Chatterjee 2010; Hevner et al. 2004).

The contribution of this design science artefact is both practical and theoretical. The practical contribution of the proposed architecture and data model and its evaluation is that it will determine the feasibility of the approach. The artefact will contribute also towards the Information Success theories (Delone and McLean 2003) and Knowledge Management Success theories (Jennex 2017), as well as the relevant theories in system usage and representation theory (Burton-Jones and Gallivan 2007; Burton-Jones and Grange 2012; Wand and Weber 1988)

Conclusion

This research in progress proposes that capturing usage information from a time-critical knowledge-based clinical decision support system, coupled with analytics can support continual improvement of the KB-DSS system. Traditional knowledge-based expert/advisory systems generally have an open-loop architecture, whereby the knowledge acquisition effort is done through consulting experts or documented information usually with the assistance of a knowledge engineer. This traditional approach is effective in situations when the knowledge-engineers have access to the relevant experts and when the relevant knowledge is documented. However, as described, research indicates that in the healthcare field the knowledge acquisition is associated with unique challenges, and often this leads to a slower pace of improvement of the associated knowledge base. This in turn may lead to lack of system use or as shown in some cases unwanted clinical outcomes. The proposed approach posits that the knowledge acquisition can be supported through the capture of usage data and analytics to improve the knowledge base.

This research will apply a design science approach to create a data model and an associated system architecture to introduce usage-driven knowledge discovery into time-critical decision support systems. The contribution of this research is both practical and theoretical.

Future extensions of this research could result in such system usage data to be stored along with or within the electronic health record. Being more than just a system audit log, the data would be stored in a format (such as de-identified records) where it could be utilized by analytics across multiple interventions. The insight gained from this information could contribute towards improving not just a single knowledge-based of a decision support but the collective use of multiple healthcare systems, which could improve the integration of knowledge across multiple healthcare domains or integrating knowledge across geographical borders.

Acknowledgements

This research (PhD) project is a collaboration with the Monash Institute of Medical Engineering (MIME).

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