Data-Driven Web-Based Intelligent Decision Support System for Infection Management at Point-Of-Care: Case-Based Reasoning Benefits and Limitations

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Abstract: Antimicrobial Resistance (AMR) is a major patient safety issue. Attempts have been made to palliate its growth. Misuse of antibiotics to treat human infections is a main concern and therefore prescription behaviour needs to be studied and modified appropriately. A common approach relies on designing software tools to improve data visualization, promote knowledge transfer and provide decision-making support. This paper explains the design of a Decision Support System (DSS) for clinical environments to provide personalized, accurate and effective diagnostics at point-of-care (POC), improving continuity, interpersonal communication, education and knowledge transfer. Demographics, biochemical and susceptibility laboratory tests and individualized diagnostic/therapeutic advice are presented to clinicians in a handheld device. Case-Based Reasoning (CBR) is used as main reasoning engine to decision support for infection management at POC. A web-based CBR-inspired interface design focused on usability principles has also been developed. The proposed DSS is perceived as useful for patient monitoring and outcome review at POC by expert clinicians. The DSS was rated with a System Usability Scale (SUS) score of 68.5 which indicates good usability. Furthermore, three areas of improvement were identified from the feedback provided by clinicians: thorough guidance requirements for junior clinicians, reduction in time consumption and integration with prescription workflow.

1 INTRODUCTION

Antimicrobials are drugs that kill or stop the growth of microbes (e.g. bacteria or viruses), thereby are commonly used to treat infections. Recently, Antimicrobial Resistance (AMR) has been reported to be a leading public health and safety problem (Wise et al., 1998; ONeill, 2014) with the inappropriate use of antibiotics in humans identified as a leading driver (Holmes et al., 2016). Microbes are continuously evolving and unnecessary antibiotic prescription, particularly within infection diseases, are a common concern in critical care and infection management, which are observing and suffering the consequences of an increased rate of AMR. In addition, failure to recognize and respond to the early stage infections is considered a major cause of avoidable mortality. Thus, it is needed to develop guidelines and software tools that facilitate healthcare professionals to treat their patients at the patient bedside by collecting and visualizing laboratory test results while providing a support system to assist in decision-making.

Antibiotic resistance is most likely to develop in areas with a considerable concentration of sick patients and high risk of infection where antimicrobials are used extensively. Henceforth, the Intensive Care Unit (ICU), where proportion of inappropriate antibiotic prescription ranges from 41% to 66%, is targeted in our preliminary studies. Handheld Decision Support Systems (DSSs) including local antibiotic guidelines have proved to reduce antibiotic prescribing in the ICU (Sintchenko et al., 2005). Despite their benefits, factors as hardware availability or interface design (Tsopra et al., 2014) obstruct the acceptance of DSSs in clinical environments. To promote their use, it is necessary to determine the best way to present the information (Moxey et al., 2010). The Healthcare Information and Management Systems Society

(HIMMS) stressed the benefits of designs based on usability principles (Belden et al., 2009). In addition, a well designed DSS sustains the advanced algorithms implemented in its core with a fully comprehensible representation to support confidence in doctors. Since medical knowledge is voluminous, it has to be focused on data and decision making while providing access to electronic health records (HER) and personal health information (PHI). Many studies show that young clinicians engage better with the use of mobile applications, displaying great potential to improve learning and augmenting traditional training (Boulos et al., 2014).

In this paper we postulated that an appropriately designed clinical information technology system could improve reliability and consistency of collecting vital signs; their visualization, interpretation and analysis; and the delivery of a more sophisticated DSS. Therefore, health care professionals and biomedical engineers from Imperial College of London have designed a prototype system accessible at the point-of-care (POC) with the specific objectives of improving three main areas: personalization and therefore outcomes of infection management; continuity through POC support for interpersonal communication; and education during interactions between clinicians and infection specialists.

2 BACKGROUND

Critical care, infection management and antimicrobial stewardship is predominantly multidisciplinary with involvement of infection specialists being crucial. In practice, antimicrobial prescribing frequently occurs out of hours, and when advice is dispensed by infection specialists, uptake can be variable. Current patient management systems rarely integrate DSSs to assist with this, or if they do, this is very basic. Therefore, there is an evident need for an intelligent clinical DSS.

2.1 Decision Support Systems

A clinical DSS can be defined as a computer program that is designed to analyse data to help health care professionals make clinical decisions. They are meant to increase quality of care, enhance health outcomes and reduce human errors while improving efficiency, cost-benefit ratio and patient satisfaction. Most basic systems include assessment, monitoring and informative tools in the form of computerized alerts, reminders and electronic clinical guidelines. For example, therapy and vital signs monitoring (McGregor et al., 2006) or susceptibility test results visualization (Flottorp et al., 2002). More advanced diagnosis and advisory tools usually rely in statistics, machine learning and artificial intelligent techniques to provide a higher level of data extraction. For example, diagnose and therapy advisers (Paul et al., 2006) or infection risk assessment (Mullett et al., 2004).

Different approaches have been used to design intelligent DSS, each one with their own benefits and drawbacks. Decision trees are popular for their simplicity to understand and construct from logical rules and have been applied in dengue fever diagnosis (Tanner et al., 2008) and antibiotic selection (William Miller, 2013). The amount of computing time required for large datasets is still reasonable. However, they do not tend to work well if decision boundaries are smooth (Quinlan, 1986) and are not optimal for uncorrelated variables. As a result of the greedy strategy applied, they also present high variance and are often unstable, tending to over-fit.

Probability-based approaches are emerging due to its capacity to represent and handle uncertainties (Pearl, 1988). Bayesian Networks (BN) are probabilistic networks that represent a set of variables (nodes) and their dependencies (arcs) using a graph. Such causal dependencies, influences or correlations are defined based on the experience of clinicians. Hence, it can be associated with a rule-based system, which uses data to refine the previously defined relationships. They have been widely exploited in health-care (Lucas et al., 2004). Particularly, Causal Probabilistic Networks (CPN) have been used to develop DSS in diagnosis of cancer (Kahn et al., 1997), ventilator-associated pneumonia (Lucas et al., 2003) and sepsis (Tsoukalas et al., 2015). Bayesian Networks offer a natural way of representing uncertainties, however an insufficient understanding of their formal meaning may give rise to modelling flaws. In particular, Causal Probabilistic Networks are best suited to tackle very specific situations as bloodstream infection (Paul et al., 2006). Unfortunately, treatment recommendation is poor since they usually prescribe broad-spectrum antibiotics (Kofoed et al., 2009). Furthermore, there is a lack of guidance to report and interpret their results by non experts.

The Case-Based Reasoning (CBR) methodology (Aamodt and Plaza, 1994) has been used to tackle problems in antibiotic therapy (Heindl et al., 1997) and molecular biology (Jurisica and Glasgow, 2004). The aim is to use previous experience in form of cases to understand and solve new problems.

2.2 Case-Based Reasoning

Case-based reasoning is a widely used approach to solve new problems based on previous experience in form of cases. It is considered as a methodology to follow rather than an algorithm in itself as shown in Figure 1. The CBR cycle is divided in four different phases. The first phase retrieves from the database those cases that are relevant based on a predefined similarity measure (e.g. euclidean distance). In the second phase, advice is commonly given by adapting or combining the solutions from the retrieved cases (i.e. antibiotic therapies). The proposed solution is incorporated to the case and saved in the database. The third phase monitors the treatment evolution to assess its outcome (e.g. success or failure). Finally, a decision to whether retain or not the case based on its reusability is made.

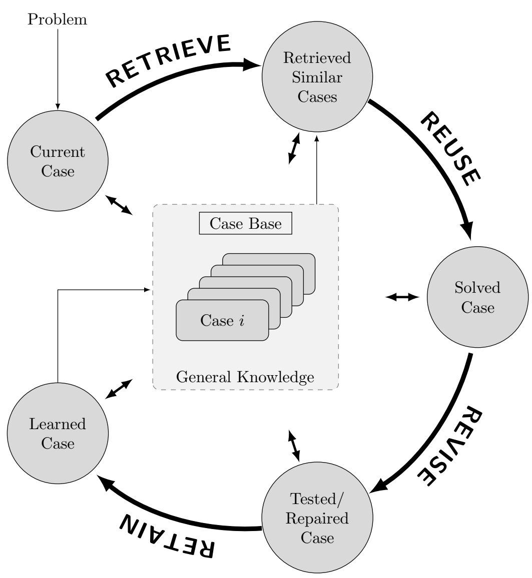

Figure 1: Diagram showing the different phases for a cycle within the Case-Based Reasoning methodology as outlined in (Aamodt and Plaza, 1994).

This methodology is very generic and can be particularized to tackle many different problems. Nevertheless, the most important property that makes CBR appropriate to be used in clinical environments is the straightforward relation that can be found between cases in the CBR methodology and cases as interpreted by clinical staff. Due to this nexus between the clinical and the scientific environments, CBR methodology has been selected to be incorporated in the decision support system and strongly influenced the design of the user interface.

3 METHODOLOGY

3.1 EPIC IMPOC

Enhanced, Personalized and Integrated Care for Infection Management at Point Of Care (EPIC IMPOC) is a decision support system designed to record a complete set of vital signs at the patients bedside on handheld computing devices while providing instant bedside decision-making assistance to clinical staff. It also pulls in data from the hospital patient administration system, laboratory results and other clinical information stored electronically. It can be used anywhere in the hospital by staff with appropriate access rights, using mobile devices or desktop computers linked to the hospital intranet. EPIC IMPOC has been preliminarily trialled at critical care antimicrobial prescribing, a known reservoir for antimicrobial resistance, and it is being extended to secondary care.

The system architecture is shown in Figure 2 were two parts are clearly differentiated: server and client sides. The server side processes queries, interacts with the permanent storage and serves web pages to the client side. The latter displays information to users. The modules constituting the server side are: *a)* CBR for history review and case comparison. *b)* Probabilistic Inference (PI) aims to provide step-wise guidance fitting the decision pathway followed by clinicians for infection management. *c)* Patient engagement module. *d)* Personalized antibiotic dosing. *e)* Visualization of Antimicrobial Resistance related information. This paper focuses exclusively on the CBR module.

3.2 Server Side

The server side has been implemented in Java and uses an object-relational mapping java library (Hibernate ORM) to map an object-oriented domain model to a traditional relational database (SQL). The Lightweight Directory Access Protocol (LDAP) accomplishes the authorization and authentication of users and it is provided in all hospitals at Imperial College Healthcare National Health Service Trust. The server side follows the REST (Representational State Transfer) architectural design, which suggests a group of guidelines to create scalable, more performant and maintainable web services.

The core CBR module implementation is based on the JColibri framework (Díaz-Agudo et al., 2007) including some improvements to achieve better generalization and performance. It is used to retrieve cases from the database based on a similarity measure. A case is defined by a compendium of parameters that

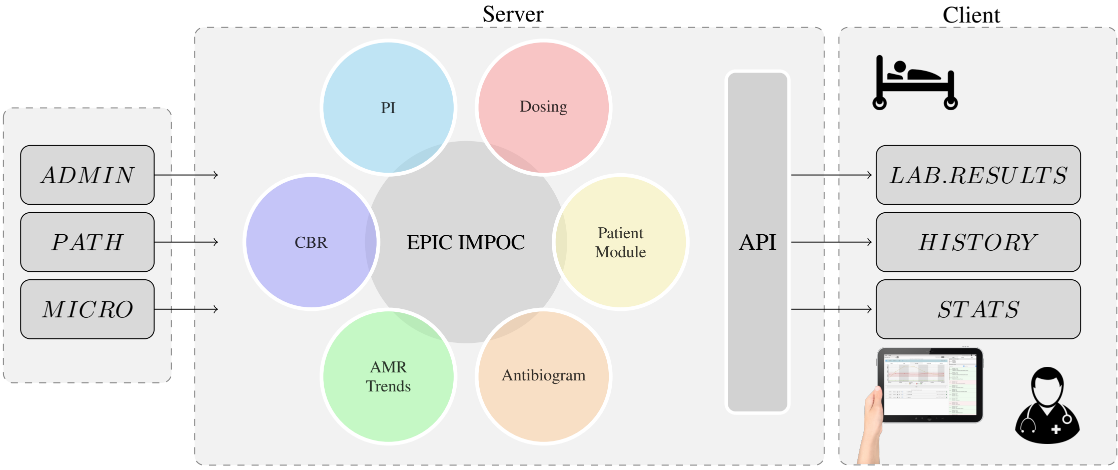

Figure 2: High-level diagram describing the main components of the DSS. The external databases that are currently being accessed are patient administration system (ADMIN), pathology laboratory tests (PATHO) and microbiology results (MICRO). The server side has the following independent modules: Case-Based Reasoning (CBR), Probabilistic Inference (PI), Patient module, Dosing module, antibiogram and AMR trends. All the information is accessed through an API and presented on a handheld device to clinicians.

can be grouped in five different sets: metadata, description, solution, justification and result. However, only those in the description container are used to compute the similarity scores. Some examples of attributes used to define the case are: demographics (age, gender or weight), existing diseases (allergies, HIV or diabetes), respiratory system (ventilation support or oxygen requirements), abdomen (abdominal examination, renal support or catheter), biochemical markers (creatinine or bilirubin) and microbiology (infectious organisms).

3.3 Client Side

The client side is a web-based application implemented using HTML, CSS and Javascript which is accessible through the browser. It follows a responsive design approach to render a consistent interface across different devices, from desktop computers to mobile phones and tablets with different screen sizes.

An efficient DSS user interface should present all the information relevant to clinicians neatly, combining different resources of patient-related information (i.e. demographic, pathology and microbiology data). Since some data might be missing or not available, it is also desired to enable clinicians to manually input data or comments for further consideration. In addition, infections evolve with time and so do treatments. Thus, inspection of previous symptoms, treatments and outcomes is desired. Since there is an straightforward relation between cases as interpreted in clinical environments and cases in the CBR methodology, a case is considered as main unit of patient related information to be presented in the interface. A single case is formed by several components, mostly regarding the type and source of the data, and has been divided in different sections (tabs in Figure 3) for visualization purposes. The *Resume* section is read-only and displays the most relevant information (e.g. infectious micro-organisms or organs infected) while *Description* shows additional information and allows the insertion/modification of parameters within the case. *Solution* contains the antibiotic therapy prescribed (including frequency, via and doses) and a section to collect feedback from users.

Six routinely requested biochemical markers were selected as main indicators of infection and patient status after reviewing the scientific literature and discussion with clinicians and infectious disease experts. The temporal evolution of such biochemical markers is shown in *Pathology* (see Figure 3) as time-series where coloured background indicates the normal reference range. Additionally, it is possible to hide/show time-series to improve visualization.

Susceptibility testing is used to determine which antimicrobials will inhibit the growth of micro-organisms causing a infection and is generally performed in vitro. The *Microbiology* section displays the result of all the susceptibility tests requested for the patient. The outcomes of the tests are provided for individual pairs (infectious organism and antibiotic) and are categorised as resistant, intermediate and sensitive. They are also presented during antibiotic therapy selection for further guidance.

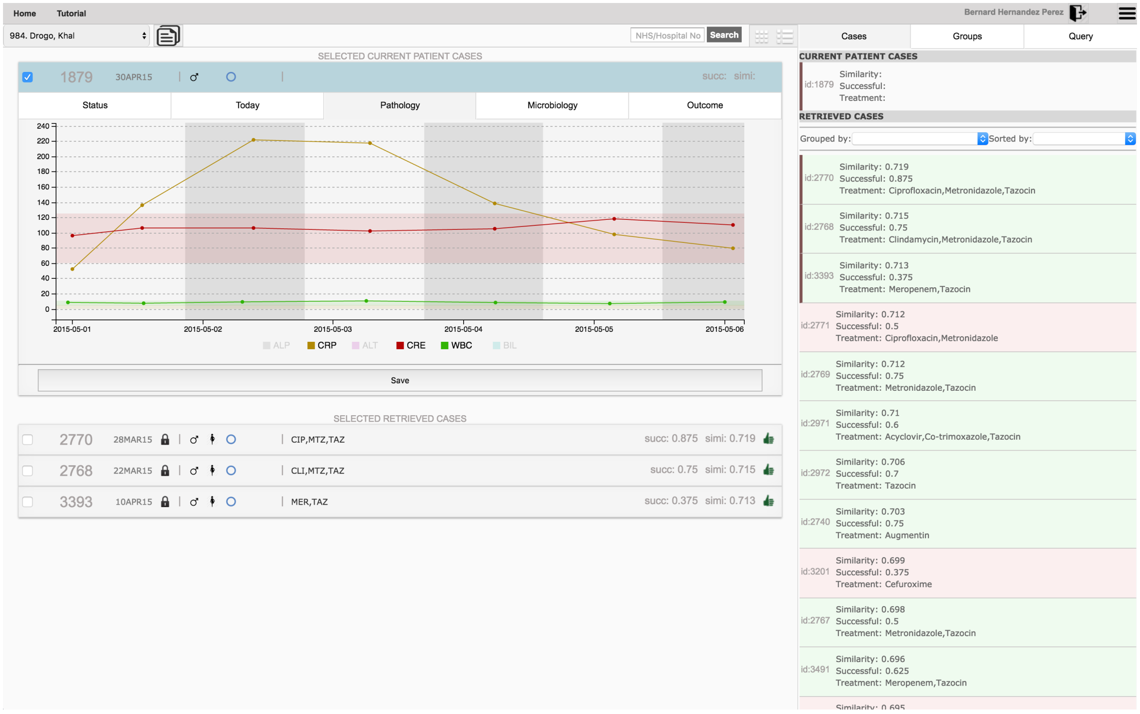

Figure 3: EPIC IMPOC web-based decision support system overview. The main unit of information is the case and its content is displayed among five different tabs (Resume, Description, Pathology, Sensitivity and Solution). The user interface is divided in three main areas: patient selection, dashboard with current patient (top) and retrieved cases (bottom), history review and a side bar to add/remove cases to/from such dashboard.

4 RESULTS

A working prototype of EPIC IMPOC incorporating Case-Based Reasoning methodology as decision-support engine was preliminarily trialled in the Intensive Care Unit at Hammersmith Hospital in London for a month. The predefined case base contained 80 cases and information retrieval was performed through handheld computer devices (i.e. ipads) at the patient bed side by clinicians under the supervision of infection specialists. From such study the following conclusions were extracted:

- The system has potential to promote and facilitate communication between nurses, clinicians and infection specialists as shown by the interaction among them during the trial.
- The system improves homogeneous collection of vital signs. Such improvement comes from the introduction of a form in the description of the case to input missing symptoms easily. The form is filled automatically for those symptoms available in external databases (e.g. electronic health records).
- The system facilitates data visualization at POC and simplifies comparison with previous similar cases and outcomes. In addition, biochemical markers evolution, susceptibility tests and history review for the hospitalized patient are easily accessible and found to be very helpful at point of care.
- The system is capable of mimicking clinicians prescription practices in the intensive care unit. In such trial clinicians were under the supervision of infection specialists. As a result, therapies prescribed by clinicians and therapies retrieved by the CBR algorithm matched approximately 90% of the times. It is especially visible in ICU where wide-spectrum antibiotics are commonly used.
- It increases and facilitates the interaction between clinicians and patients. Therefore it helps engaging with patients and opens the possibility to educate population on antibiotic misuse and its consequences (Rawson et al., 2016b).

4.1 System Usability Scale Survey

A survey to evaluate the usability of the decision support system interface was performed. The System Usability Scale (SUS) (Brooke et al., 1996) is composed of 10 statements to which participants indicate their agreement from 1 to 5, where 5 indicates strongly

Table 1: The original SUS statements (Brooke et al., 1996), average agreement and SUS contribution.

SUS statements	Avg. rating	SUS contribution
I think that I would like to use this system frequently.	2.8	1.8
I found the system unnecessarily complex.	1.4	3.6
I thought the system was easy to use.	2.0	1.0
I think that I would need the support of a technical person to be able to use this system.	1.6	3.4
I found that the various functions in this system were well integrated.	3.0	2.0
I thought that there was too much inconsistency in this system.	0.2	4.8
I would imagine that most people would learn to use this system very quickly.	2.8	1.8
I found the system very cumbersome to use.	2.2	2.8
I felt very confident using the system.	3.0	2.0
I needed to learn a lot of things before I could get going with this system.	0.8	4.2

agree. Predefined rules for positive and negative statements are used to obtain the SUS contributions. The SUS contribution for each statement ranges from 1 to 4 where higher scores indicate better usability (see Table 1) and their sum is multiplied by 2.5 to calculate the final SUS score. It ranges from 0 to 100 where poor and great product usability are indicated for SUS scores under 50 and over 80 respectively. This survey is technology agnostic, quick, provides a single score and is non proprietary. A free-text box was added for additional comments and suggestions.

The SUS survey was completed by 10 different participants (83% males) from 27 to 51 years old where technical training in the use of the system was not provided. The profile of those participants was infection specialist (two), clinician (three), nurse (four) and other staff (one). The SUS contribution for each statement is presented in the right column in Table 1. The final SUS score obtained is 68.5 which indicates good product usability with margin to improve. Additionally, a variety of comments were provided by participants and have been synthesized in the following bullet points:

- There is a common concern among experienced clinicians and infection specialists in the use junior doctors would do of such large amount of data displayed in the interface. The decision support system has potential to help training junior doctors and improve their prescription practices, but it needs to narrow the presented information providing specific guidance.
- Clinicians consider the user interface intuitive and helpful for patient long-term monitoring and management, however it might sometimes be time consuming. Additionally, it does not entirely fit with the work-flow followed to prescribe antibiotic therapies.
- They suggested the possibility of recording further parameters, not necessarily directly related with infections.

From the preliminary trial performed by infection specialists and the feedback obtained from the surveys, it is possible to conclude that the CBR algorithm is able to mimic the prescription practices of users. However, that is not enough to promote change in antibiotic prescription practices. Initially, as a quick solution infection specialists were keen in creating an "ideal" case base; that is, a set of cases with optimal antibiotic therapies according to infection guidelines and expert prescriptions. Such optimal therapies would then be suggested by the decision support system to further users. Hence, the knowledge would be transferred from infection specialists to other clinical staff (e.g. nurses and clinicians).

Unfortunately, this approach presents several drawbacks. Creating a complete case base that covers the whole spectrum of possibilities is nearly impossible and time consuming. In addition, infections are often acquired in hospitals by contagious as a consequence of treating more severe diseases which diminish the immune system (e.g. surgeries and cancer). Therefore, future therapies prescribed by clinicians and recorded in the system might not agree with the infection guidelines reshaping the case base and therefore altering CBR recommendations. A case base with strictly guideline oriented therapies on the long-term is unrealistic and limits the scope and usability of the system.

After discussion with a multi-professional team including physicians, nurses, pharmacists and non-medical researchers, an study to map the pathway followed by clinicians to prescribe antibiotics therapies was performed (Rawson et al., 2016a). The reported infection management pathway was defined as a stepwise Bayesian model of estimating probabilities in which each step adds systematically information to allow optimisation of decisions on diagnosis and management of infection. Initially, clinicians estimate the risk of infection and attempt to localize its source by looking at patient's physiological parameters. Once clinicians construct a picture of the severity of the infection, whether or not to initiate antimicrobial therapy is decided. In this step, local microbiology guidance provided within hospitals was the most commonly cited factor. Finally, they review and refine the treatment accordingly.

This new approach enables to produce very specific step-by-step probability-like decision support. This would improve the guidance provided to junior clinicians and facilitates the validation of decision-making for each individual step. Additionally, since reviewing of previous cases is not necessary it would greatly reduce usability time. Since the methodology integrates with the infection management pathway, it will likely influence prescription practices to a higher degree than CBR.

5 DISCUSSION

DSSs are being exploited in several areas such as business or economics but their acceptance by clinical staff is obstructing its use in hospitals and other clinical environments (Kawamoto et al., 2005). Designing a DSS based on usability principles and simply providing the clinical information does not guarantee acceptance (Moxey et al., 2010). Other factors as accessibility, availability, easy of use, time requirements and integration into the clinical workflow are important and need to be considered (Tsopra et al., 2014). Taking previous knowledge in consideration, a DSS to support prescription of antibiotic therapies and patient monitoring at POC exploiting the CBR methodology was implemented.

In many circumstances, as complicated cases, providers prefer to consult their colleges or more specialised clinicians as infection specialists. This consultation among different members of the clinical staff was facilitated by the DSS. In addition, it was believed to enhance decision making and homogeneous collection of vital signs among clinicians resulting in better prescribing practices. Furthermore, re-entering patient data to generate advices is a deterrent to use (Moxey et al., 2010) and integration into existing programs (e.g. electronic medical records) was a clear facilitator.

The usability measured through the SUS survey was 68.5 which is about average and shows potential margin for improvement. A similar strength of agreement was shown by participants for the third and eight statements which had an average rating of 2.0 and 2.2 respectively. The SUS contribution for each statement was 1.0 and 2.8 respectively, indicating that the system is usable but not necessarily easy. Note that some wording used by the original SUS was suggested to be poorly understood by participants affecting the results (Bangor et al., 2008). As an example, the sixth statement which contributed the most contains the wording “too much” which might be unclear. Additionally, users may not have a good sense of the required complexity of such systems since there are no commonly known competing solutions and the wording “unnecessarily” in the second statement might have led to a higher contribution of 3.6. Therefore, the final SUS score is possibly slightly less that the one presented.

There is still much to be done to make these system work in routine clinical practice. Measuring absolute usability using a single metric is very challenging since many external factors influence the results (e.g. technical training or accessible technology). The feedback provided greatly helped to identify areas of improvement and the results of the survey are a useful source for future comparison to asses the benefits of including new components to tackle the identified weaknesses.

6 CONCLUSIONS

CBR methodology was incorporated in a DSS as decision-making engine providing similar antibiotic therapies to those prescribed by expert clinicians in the majority of cases in our preliminary trials. In addition, it was widely accepted for information retrieval and long-term patient monitoring and management. Three main areas of improvement were identified from the feedback provided by expert clinicians: specific guidance requirements for junior clinicians, a need to reduce time consumption using the DSS and a better integration into clinical workflow.

The reported infection management pathway was defined as a multi-step Bayesian-like approach (Rawson et al., 2016a) which inherently tackles most of the weaknesses identified: specific guidance, time constraints and integration in the workflow. Therefore, it is more suitable to support and modify prescription practices.

The combination of both approaches into one single decision support system is a very elegant solution that could lead to an increase in acceptability among clinicians. To validate its feasibility, infection risk and source of infection inference from biochemical markers are considered as primary steps. The final integration of such inference in the user interface has potential to reduce misuse of antibiotics and its evaluation forms the basis for future work.

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