International Journal of Medical Informatics (2003) **70**, 309–316

International Journal of Medical Informatics

www.elsevier.com/locate/ijmedinf

Which clinical decisions benefit from automation? A task complexity approach☆

Vitali Sintchenko*, Enrico W. Coiera

Centre for Health Informatics, University of New South Wales, Sydney 2052, Australia

Received 14 February 2003; received in revised form 26 March 2003; accepted 2 April 2003

KEYWORDS
Medical decision-making;
Task complexity;
Computerised decision support;
Antibiotic prescribing

Summary *Objective*: To describe a model for analysing complex medical decision making tasks and for evaluating their suitability for automation. *Method*: Assessment of a decision task's complexity in terms of the number of elementary information processes (EIPs) and the potential for cognitive effort reduction through EIP minimisation using an automated decision aid. *Results*: The model consists of five steps: (1) selection of the domain and relevant tasks; (2) evaluation of the knowledge complexity for tasks selected; (3) identification of cognitively demanding tasks; (4) assessment of unaided and aided effort requirements for this task accomplishment; and (5) selection of computational tools to achieve this complexity reduction. The model is applied to the task of antibiotic prescribing in critical care and the most complex components of the task identified. Decision aids to support these components can provide a significant reduction of cognitive effort suggesting this is a decision task worth automating. *Conclusion*: We view the role of decision support for complex decision to be one of task complexity reduction, and the model described allows for task automation without lowering decision quality and can assist decision support systems developers.

1. Introduction

There is a need to improve clinical decision-making in order to reduce practice variation, preventable medical errors and support the delivery of evidence-based medicine [1,2]. Information technology has been recognised as a key enabler in the improvement of clinical decision quality [3]. However, the decision to use technology in support of clinical decision making is itself often empirical rather than guided by sound theoretical principles. It thus remains unclear when technology should be brought in to support decision-making for complex clinical problems. Not surprisingly, information-technology initiatives have provided mixed results and the uptake of decision aids by clinicians has been slow [3–5].

The decision to select one task over another for computational support should be based on some principled methods [6]. The effectiveness of instructional aids and decision support systems (DSS) is predicated on their usefulness in addressing the specific problems that lead to sub-optimal decisions [7]. The objective of our study is to design a framework for the rational selection of clinical tasks for automation using a cognitive task com-

☆ This paper was presented at the MIE2002.

*Corresponding author. Tel.: +61-2-9385-1269; fax: +61-2-9385-1813.
E-mail addresses: v.sintchenko@unsw.edu.au (V. Sintchenko), ewc@pobox.com (E.W. Coiera).

1386-5056/03/$ - see front matter © 2003 Published by Elsevier Ireland Ltd.
doi:10.1016/S1386-5056(03)00040-6

plexity approach and to investigate its potential benefits.

2. Theoretical framework

Task complexity affects information use and has been shown to be one of the important determinants of decision-making efficiency [8]. Based on a cognitive engineering approach, Woods postulated that all tasks contain three essential components such as products, required acts, and information cues [9]. He has argued that complexity describes the relationships between acts and information cues as task inputs and has used these components to derive three dimensions of task complexity: component complexity, coordinative complexity and dynamic complexity. Each dimension can be characterised by a sum of cognitive efforts needed to accomplish the task [9]. Component complexity represents the number of cognitive acts that need to be executed to accomplish the task and the number of information cues that must to be processed in this process. Coordinative complexity refers to the nature of relationship between task inputs and products. For example, a prescribing task in a case of a patient on a ventilator with multi-organ failure has higher coordinative complexity that the same task for a patient with uncomplicated mild infection in general practice. Dynamic complexity reflects the speed of changes in patient's condition or clinical evidence.

We adapted and extended a framework presented by Payne et al. [10] to prescribing decisions. In this framework, decision strategies are evaluated along two dimensions: the amount of effort required to perform the strategy and the decision quality attained by using the strategy. Quality of the strategy is measured by comparing the choice or outcome from applying the strategy to the outcome from a normative strategy. Cognitive effort is typically measured in terms of number of elementary information processes (EIPs), which are basic units of thought needed to complete a decision problem (e.g. comparing two values, reading the value, retrieve the value, etc). The strategy usually employed as the normative benchmark for preferential choice problems is the weighted-additive (WAD) model.

The assessment has the following stages: (1) selection of the domain and relevant tasks; (2) evaluation of the knowledge complexity for clinical tasks selected; (3) selection of potentially most cognitively demanding task; (4) assessment of unaided and aided effort requirements for this task accomplishment; and (5) selection of computational tools to achieve this task complexity reduction (Fig. 1). If decision support is not reducing a complex task into a simple one, without loss of the decision quality, than the performance of the task in question is unlikely to benefit from automation. We postulate that this model accurately estimate the extent of cognitive complexity reduction provided by automated decision support.

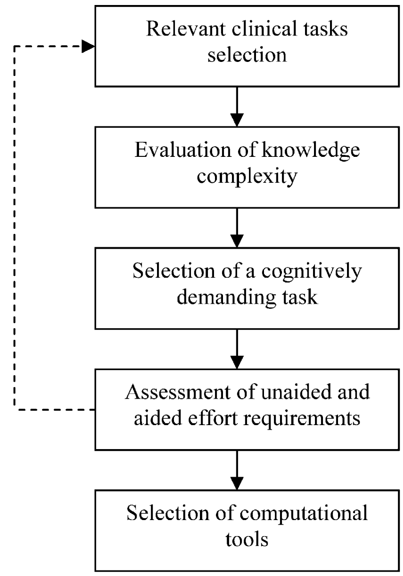


Fig. 1 Task complexity model for optimal task selection.

3. Choice of the domain

Prescribing is an activity central to clinical practice [11]. The prescribing task in critical care is accomplished under time pressure and with limited diagnostic information. Infection is a common presenting problem and antimicrobials are among the most frequently prescribed drugs. Therefore antibiotic use has long been considered an important target for analysis of decision-making [11]. Several studies demonstrated significant level of antibiotic misuse ranging at university medical centres from 41 to 66% [12,13].

Prescribing decisions in critical care are made in a specialised, complex, networked environment with growing demand to improve effectiveness and measurable productivity. Decision support in this environment must consider who is a decision-maker for particular type of decision, and what type of information is required for effective decision making.

Antibiotic administration in an intensive care unit is an example of a cognitively intense task. We begin our analysis of decision complexity by comparing the tasks of management of ventilator-associated pneumonia (VAP), sepsis and central venous line–related infection (CVL). Each has a high prescribing load, variability of treatment approaches and limited specificity of clinical diagnosis, thus suggesting the need for additional information support [11]. For the purpose of this exercise we estimated task complexity by a set of measures based on three basic components of decision-making [9,14]: (1) the 'raw' data used measured by breadth of information inputs (component complexity), (2) the existing knowledge of the domain measured by scores of the rate of change in the given domain and of the medical consensus on the management (dynamic complexity), and (3) the interpretation and synthesis of that information by applying knowledge to come to the decision (coordinated complexity), measured by scores of interpretation required for information inputs and decision impact on clinical outcomes. Three local expert-clinicians (one intensivist and two infectious diseases physicians) provided scores using the methodology described in [14]. Fig. 2 summarises the scores we assigned to these measures based upon local expert consensus and demonstrates that prescribing for VAP and sepsis are associated with cognitively complex decisions (total score more than 10). Management of VAP appeared to be the most cognitively demanding and is thus chosen for further evaluation in the remainder of this paper.

4. Prescribing effort and quality

We have constructed a prescribing decision tree that incorporates the two main management strategies ('treat first' and 'test first and treat after') for suspected VAP (Fig. 3). It is structured around the prescribing sub-goals: (1) control of potentially treatable infection; (2) prevention/delay of antibiotic resistance; (3) reduction of drug-related adverse effects; (4) prevention of super-infection with multi-resistant microorganisms [15]. This decision tree allows the calculation of the cognitive effort required for prescribing decisions based on the different decision strategies. A particular decision strategy is defined in terms of a specific collection and sequence of EIPs that are sequences of the following primitives: *read*, *retrieve*, *move*, *add*, *multiply*, *compare*, *store* and *eliminate* [16]. We now compare three decision-making strategies: weighted additive (WAD), elimination-by-aspect (EBA), and random choice (RC) strategies.

The WAD strategy considers the value of each attribute on each alternative in the decision tree. The expected utility value for each alternative is computed by multiplying the path probability of an outcome by its utility and summing the products over the outcomes as above. The alternative with a highest expected utility is chosen. The WAD strategy involves reading processes for all attributes, a number of adding and multiplying processes to fold back the decision trees and some comparisons. The cognitive effort in EIPs for the WAD strategy has been calculated as follows:

1) EIPs for computing a weighted score for a survival when infection is treated: *move* to the probability of controlling infection, *read* it, *retrieve* the probability of infection, *multiply* these two probabilities, *and store* the result. Five operations are involved. To calculate the path probability of survival *move* to the probability of survival, *read* it, *retrieve* the stored result, *multiply* it by the probability of survival and *store* the result. Repeat these operations for each of 44 tree branches to calculate path probabilities for each of 24 outcomes. Thus, the EIPs required for this stage are $5 \times 44 = 220$.

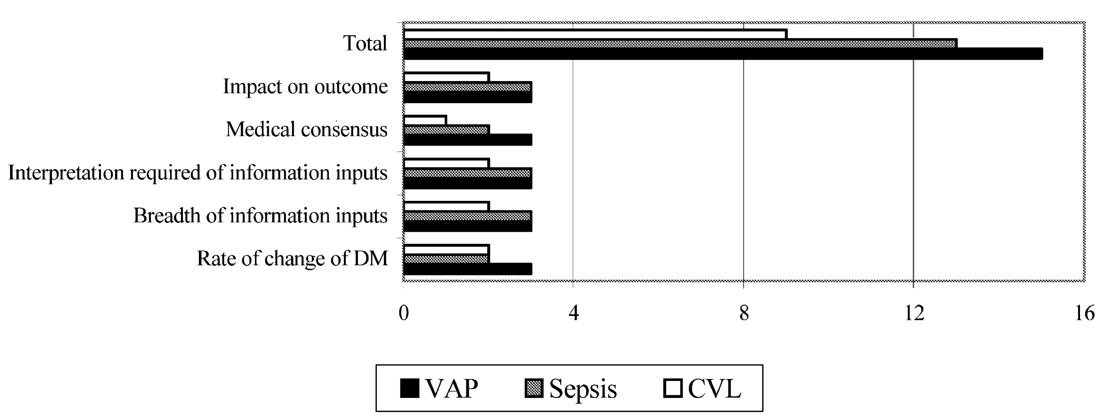


Fig. 2 Expert task complexity assessment. DM, decision domain.

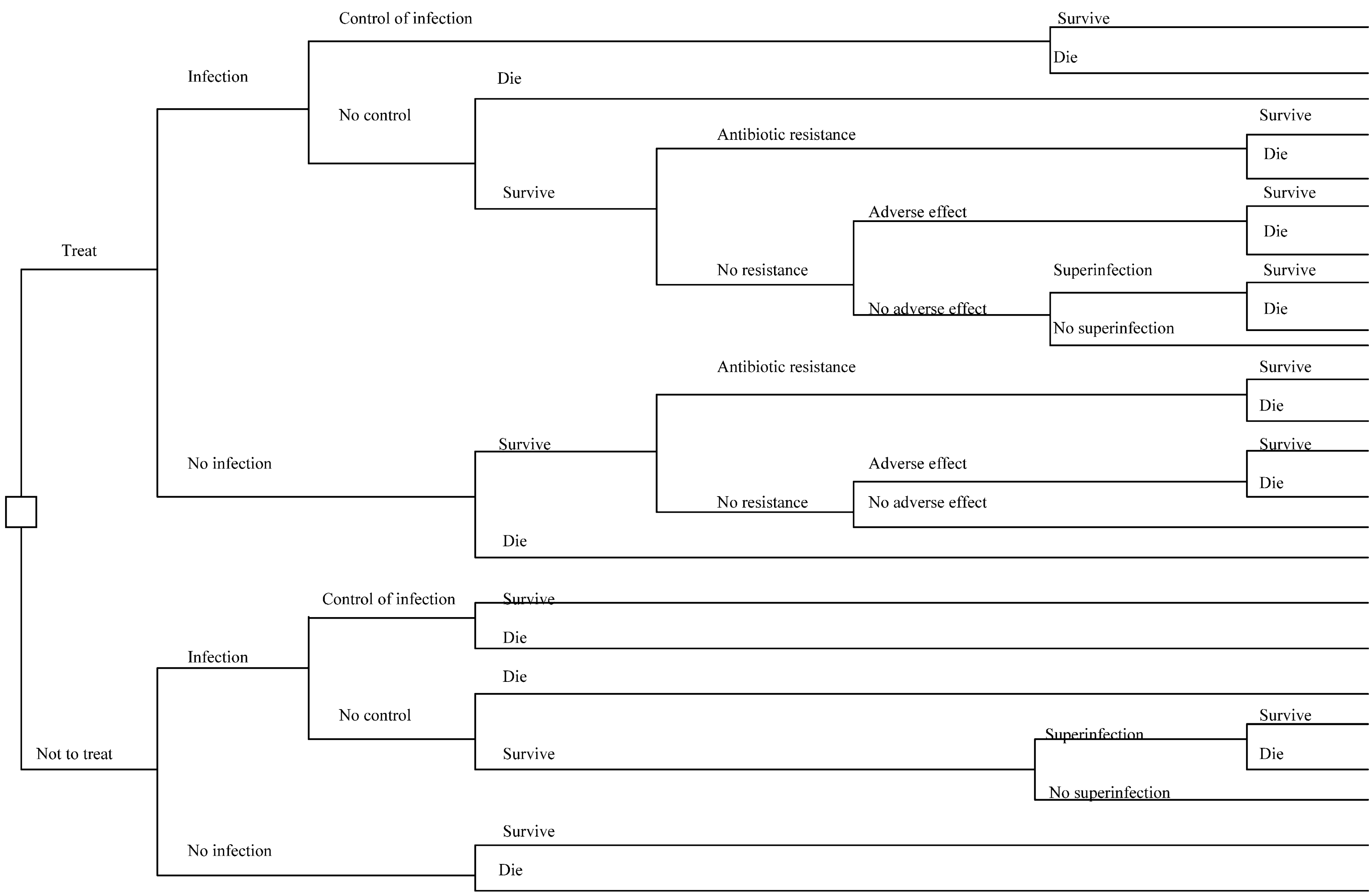


Fig. 3 Decision tree for 'treat with antibiotics' and 'test first and treat with antibiotics after' strategies for the management VAP in critically ill.

2) EIPs for computing expected utilities of the outcome: *retrieve* path probability and *retrieve* the utility for the outcome, *multiply* them, *store* the result. For 24 outcomes the score $24 \times 4 = 96$.
3) EIPs for computing a weighted expected utility for the first alternatives: *add* expected utility scores to obtain a total score, *store* the total score. Thus, the EIPs required to compute a weighted score for the first and second alternatives are, respectively $(11-1)+1=11$ and $(7-1)+1=7$. EIPs for finding the alternative with the highest expected utility: *retrieve* the expected utility of the first alternative, *retrieve* the expected utility for the second alternative, *compare* them, and *eliminate* the alternative with the lower score. Four operations are involved. Total number of EIPs is $220+96+17+7+4=344$. With the decision support aid, only 17 EIPs (retrieving, comparing and eliminating utilities for 6 possible outcomes) are required.

In contrast, the EBA strategy has fewer reading processes because the outcome utilities are not considered. The EBA strategy identifies only the most important attributes and all alternatives with a value higher than some 'cutoff' are retained for further consideration. To evaluate a single attribute a decision-maker must read the attribute value, compare it to the threshold, and eliminate the alternative if the attribute fails to meet the threshold. Attributes are chosen for evaluation based on their relative importance to the decision-maker [17]. The EIP calculation for EBA strategy is based on the formula [16]: $(1 \times n)+(1 \times (n-1) \times m)+(4 \times (m \times n))$ where n is the number of decision branches and m is the number of decision attributes. The formula sums the EIPs for the three operations of retrieving, tracking and evaluating each decision tree branch. For four attributes (control of infection, adverse effects, development of resistance and superinfection) and eight branches it will be $1 \times 8+(1 \times (8-1) \times 4)+(4 \times (4 \times 8))=8+28+128=164$. The total number of EIPs for our EBA decision tree is thus 164.

Finally, the random choice strategy is a 'tossup' between two options (treat or not treat) and does not require any cognitive effort. The WAD model, while providing for highest decision quality, if unaided is very effortful (Fig. 4). The EBA strategy, on the other hand, requires less effort and is commonly used by decision-makers, but provides only about 70% quality. Decisions strategies that require more than 100 EIPs are considered to be complex [16]. In our case, a prescribing decision

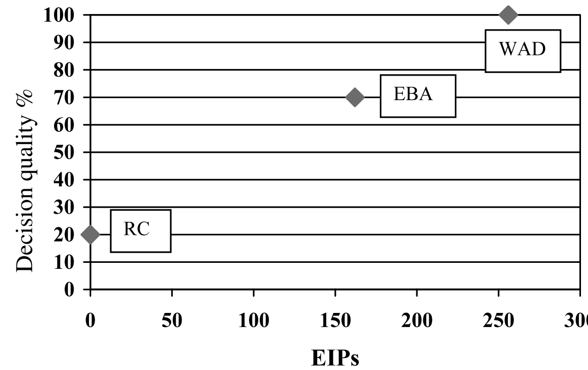


Fig. 4 Effort and decision quality tradeoffs for prescribing decision strategies. The x-axis represents quality relative to the weighted-additive strategy (WAD) normative model. EBA, elimination by aspect strategy; RC, random choice strategy.

based on the WAD and EBA strategies required 344 and 164 EIPs, respectively. Having analysed the EBA decision tree, we concluded that majority (62%) of cognitive effort is associated with the calculation of path probabilities of prescribing outcomes. Provision of these probabilities by a decision aid would reduce the total cognitive effort to 17 EIPs, transforming a complex cognitive task into a simple one and whilst retaining maximum decision quality. Table 1 illustrates this task complexity reduction strategy.

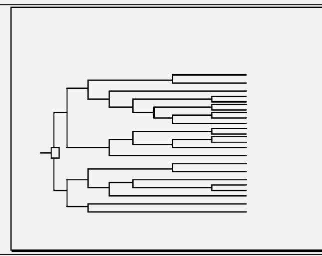
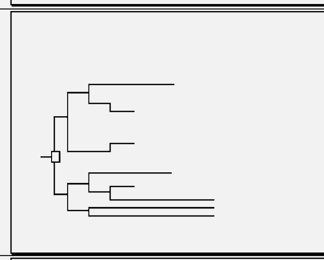
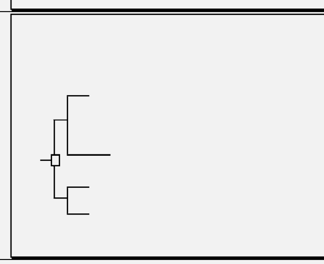
Consequently it appears rational to develop automated aids to support this prescribing decision, specifically in assisting clinicians to calculate path probabilities. Two screenshots from such a decision aid designed by our group to support antibiotic prescribing in critical care by providing VAP risk assessment [18] are shown in Fig. 5.

5. Discussion and conclusions

We argue that prescribing is a complex clinical task because it involves: (a) integration of complex information from a variety of sources; (b) incomplete or imperfect information; (c) the presence of uncertainty and time pressure; (d) a complex interaction between the clinician and the patient with different utilities and values to the alternatives in the decision.

Such high complexity is a general risk factor in clinical decision making. It has, for example, been suggested that clinicians choose less cognitively demanding strategies when making decisions under uncertainty and time pressure [19], and task complexity has been found to affect information acquisition and prescribing decisions [20]. The targeted use of computerised decision support

Table 1 The comparison of total cognitive effort required by decision-making strategies without (WAD and EBA) and with decision-support

Strategy	Decision tree	Total cognitive effort*
Weighted additive strategy		344
Elimination-by-aspect strategy		164
Use of the decision aid		17

* - Calculation of path probabilities and expected utilities, EIPs

may be viewed as a strategy to maintain decision quality under such conditions of reduced cognitive resource. Although evidence to support this hypothesis is accumulating, more research is needed to explore the relationship between task complexity, decision support seeking and subsequent decision quality. This knowledge is critical for the

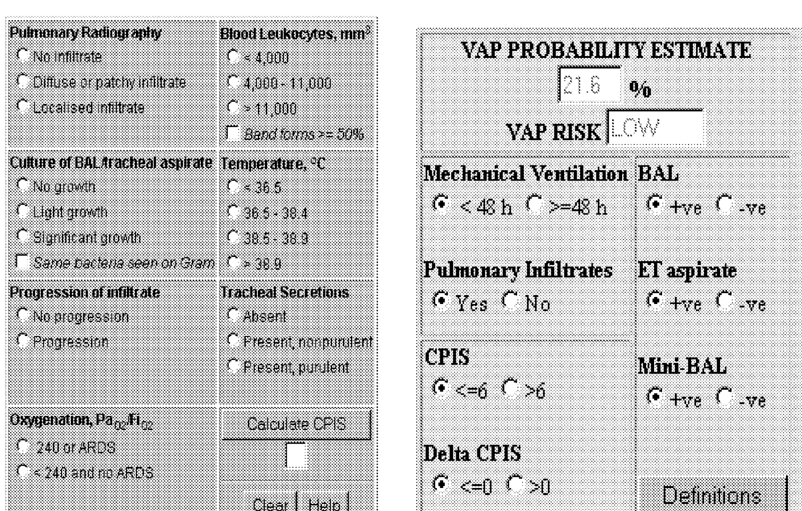


Fig. 5 Screenshots of VAP risk assessment tool.

development of successful interventions that change health care practitioners' behaviour.

Decision aids can be used to reduce the relative effort needed for decision [17]. The nature and number of EIPs required to execute the best quality strategy coupled with task analysis results provide an environment for rational design of decision support system. The framework described here suggests a simple algorithm for such task selection that itself can be automated. This framework is based on the idea of decision support as task complexity reduction without sacrificing the quality of decision-making model. Furthermore, it facilitates a form of decision aiding based on information processing as opposed to more traditional aids based on the evaluation stage of decision behavior. This framework illustrates conceptually a choice of a decision strategy, has a potential for decision-maker utility preferences inclusion into DSS design, and can be used to predict which task computation may be beneficial. Computerised decision support may assist physicians in high frequency, urgent and complex tasks and be a useful tool to reduce antibiotic misuse.

We have chosen antibiotic prescribing task in critical care as an example to outline main steps of suggested model. However, we believe that framework described may be generic. Other clinical tasks may provide additional challenges in their complexity assessment.

Another limitation of our approach is that task complexity arises from the mutual impact of task model and the decision environment. A complex task may have large number of subtasks, inputs and products with elements that are probabilistic in their behaviour and may evolve over time, making it hard to model the task in the explicit way described here. Hence, task complexity must be understood to arise out of a given situation and include the interactions between task attributes and the individual decision maker's attributes.

This point of view is supported by the emergence of *interaction design* as a new paradigm to describe the way information and communication systems are conceived [21]. Interaction design emphasises that people and machines together constitute an information system, and that we must not just model decisions and tasks, but the cognitive attributes of humans, if systems are to succeed in complex organisational environments. The conceptualisation of decision task complexity proposed here may lead to a new way of thinking about the components of task complexity and the need for their integration in support of appropriate interaction design with decision tools.

Finally, although it is beyond the scope of this paper, it seems natural to generalise the framework described as a strategy for task-centred decision support, based on the idea of controlled complexity reduction. Our current research is directed at exploiting task complexity characteristics in the challenging areas of requirements engineering and the point-of-care clinical decision-support for prescribing task.

References

[1] R.M. Poses, R.D. Cebul, R.S. Wigton, You can lead a horse to water — improving physicians' knowledge of probabilities may not affect their decisions, Med. Dec. Making 15 (1995) 65–75.

[2] B.H. Bornstein, A.C. Emier, Rationality in medical decision-making: a review of the literature on doctors' decision-making biases, J. Eval. Clin. Pract. 7 (2001) 97–107.

[3] D.W. Bates, M. Cohen, L.L. Leape, J.M. Overhage, M.M. Shabot, T. Sheridan, Reducing the frequency of errors in medicine using information technology, J. Am. Med. Inform. Assoc. 8 (2001) 299–308.

[4] G.P. Browman, Improving clinical practice guidelines for the 21st century: Attitudinal barriers and not technology are the main challenges, Intern. J. Health Technol. Assess. Health Care 16 (2000) 959–968.

[5] H. Heathfield, D. Pitty, R. Hanka, Evaluating information technology in health care: barriers and challenges, Br. Med. J. 316 (1998) 1959–1961.

[6] E. Coiera, When conversation is better than computation, J. Am. Med. Inform. Assoc. 7 (2000) 277–286.

[7] V. Patel, D. Kaufman, Medical informatics and the science of cognition, J. Am. Med. Inform. Assoc. 5 (1998) 493–502.

[8] K. Bystrom, K. Jarvelin, Task complexity affects information seeking and use, Inf. Process. Manage. 31 (1995) 191–213.

[9] R.E. Wood, Task complexity: definition of the construct, Organ. Behav. Hum. Dec. Process. 37 (1986) 60–82.

[10] J.W. Payne, J.R. Bettman, E.J. Johnson, The Adaptive Decision Maker, Cambridge University Press, New York, 1993.

[11] C.P. Bradley, Decision making and prescribing patterns — a literature review, Fam. Pract. 8 (1991) 2762–2787.

[12] D.G. Maki, A.A. Schuna, A study of antimicrobial misuse in a university hospital, Am. J. Med. Sci. 275 (1978) 271–282.

[13] M. Thuong, F. Shortgen, V. Zazempa, E. Girou, C.J. Soussy, C. Brun-Buisson, Appropriate use of restricted antimicrobial agents in hospitals: the importance of empirical therapy and assisted re-evaluation, J. Antimicrob. Chemother. 46 (2000) 501–508.

[14] M.H. Meyer, K.F. Curley, The impact of knowledge and technology complexity on information system development. http://www.cba.neu.edu/ ~ mmeyer/research/6/article9/article.html [Accessed online on 7th of February 2003].

[15] V. Sintchenko, J.R. Iredell, G.L. Gilbert, E. Coiera, What do physicians think about evidence-based antibiotic use in critical care? A survey of Australian intensivists and infectious disease practitioners, J. Intern. Med. 31 (2001) 462–469.

[16] P.C. Chu, E.E. Spires, The joint effect of effort and quality on decision strategy choice with computerised decision aids, Dec. Sci. 31 (2000) 259–292.

[17] P. Todd, I. Benbasat, Evaluating the impact of DSS, cognitive effort, and incentives on strategy selection, Inform. Syst. Res. 10 (1999) 356–374.
[18] V. Sintchenko, H. Garsden, Clinical decision support: New approach to usability study. In: R.M. Ribbons, V. Dall, R. Webb (Eds.), Improving quality by lowering barriers/Proceedings of the 10th National Health Informatics Conference. Melbourne, 4–6 Aug 2002, pp. 14–15.
[19] A.S. Elstein, Heuristics and biases: selected errors in clinical reasoning, Acad. Med. 74 (1999) 791–794.
[20] V. Chinburapa, L.N. Larson, M. Brucks, J.L. Draugalis, J.L. Bootman, C.P. Puto, Physician prescribing decisions: the effects of situational involvement and task complexity on information acquisition and decision making, Soc. Sci. Med. 36 (1993) 1473–1482.
[21] E. Coiera, Interaction design theory, Int. J. Med. Inform. 69 (2003) 205–222.