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Which clinical decisions benefit from automation? A task complexity approach

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Abstract. This paper describes a model for analysing medical decision making tasks and evaluation of their suitability for automation. The overall approach focuses on the assessment of decision complexity and possible reduction of human effort by automated decision support. The approach consists of five subsequent steps: (1) selection of the domain and relevant tasks; (2) evaluation of the knowledge complexity for 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 complexity reduction. The model described allows for task automation without lowering of decision quality.

1. Introduction

The decision to select one task over another for computational support should be based on some principled methods [1]. The rationale for automating decisions using computer tools is based upon the poor performance of humans when faced with these tasks in clinical setting. 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 [2]. In this paper, we present research related to the task of antibiotic prescribing in the critical care setting as model domain for cognitively demanding decision-making. The objective of our study was to rationalise selection of clinical tasks for automation using cognitive task complexity approach.

2. Theoretical framework

We adapted and extended a framework presented by Payne *et al.* [3] 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 (EPIs), 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 problem is the weighted-additive (WAD) model.

The complexity 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 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 will be able to evaluate the extent of cognitive complexity reduction provided by automated decision support.

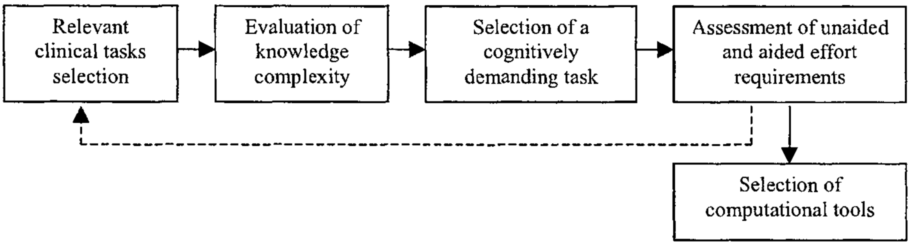

Figure 1: Task complexity model for optimal task selection

3. Choice of the domain

Antibiotic administration in an intensive care unit (ICU) is a cognitively intense task. We have chosen to compare 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. For the purpose of this exercise we estimated task complexity by a set of measures based on three basic components of decision-making [4]: (1) the decision maker knowledge of the domain measured by scores of the rate of change in the given domain and of the medical consensus on the management, (2) the "raw" data used measured by breadth of information inputs, and (3) the interpretation and synthesis of that information by applying knowledge to come to the decision, measured by scores of interpretation required for information inputs and decision impact on clinical outcomes. Fig. 2 summarises 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 most cognitively demanding and has been chosen for further evaluation.

4. Prescribing effort and quality

We have constructed a prescribing decision tree that incorporates two main management strategies ("treat first" and "test first and treat after") for suspected VAP (Fig. 3). It is based on main prescribing sub-goals revealed by experts: (1) control of potentially treatable infection; (2) prevention/delay of antibiotic resistance; (3) reduction of drug-related adverse effects; (4) prevention of superinfection with multi-resistant microorganisms. This decision tree allows calculation of the cognitive effort required for prescribing decisions based on different decision strategies. A particular decision strategy is defined in terms of a specific collection and sequence of EIPs which are sets the following primitives: *read*, *retrieve*, *move*, *add*, *multiply*, *compare*, *store* and *eliminate*.

We compare three decision-making strategies: weighted additive (WAD), elimination-by-aspect (EBA), and random choice (RC) strategies. 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. In contrast, EBA strategy has fewer reading processes because the outcome utilities are not considered. The WAD strategy is a compensatory strategy that considers the value of each attribute on each alternative. 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 (see Appendix). The alternative with a highest expected utility is chosen.

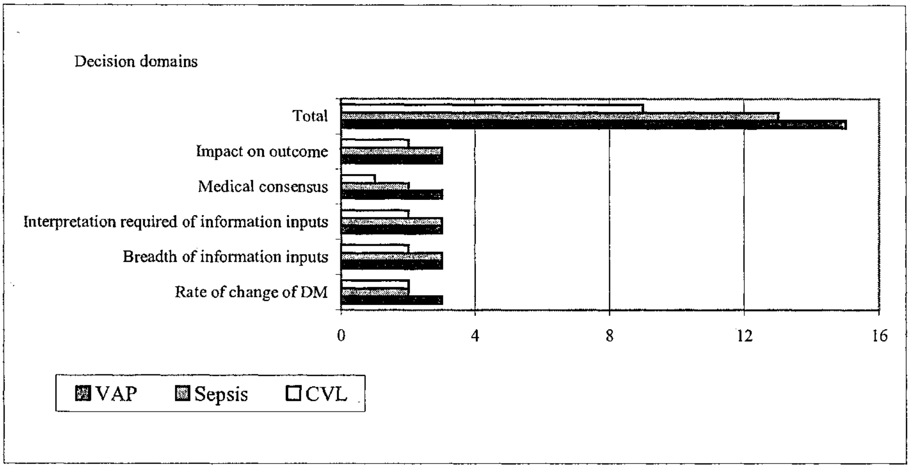

Figure 2: Expert task complexity assessment. DM, decision domain

The EBA strategy identifies only the most important attribute and all alternatives with a value higher than some 'cutoff' are retained for further consideration. The EIP calculation for EBA strategy is based on the formula given [5]: (1*n) + (1*(n-1) *m)+(4*(m*n)). Total number of for our decision tree is 162. Random choice 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 EPIs are considered to be complex [5]. In our case, prescribing decision based on WAD and EBA strategies required 254 and 162 EIPs, respectively. Decision support reduced total cognitive effort to 17 EPIs, transforming a complex cognitive task into a simple one and making the maximum quality decision achievable. Having analysed decision tree we concluded that majority (62%) of cognitive efforts were associated with the calculation of path probabilities of prescribing outcomes.

5. Conclusions

The nature and number of EIPs required to execute the best quality strategy coupled with task analysis results provided an environment for rational design of decision support system. Framework described here suggests a simple algorithm for such task selection that itself can be automated. 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 behaviour. This framework as presented is useful because it 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.

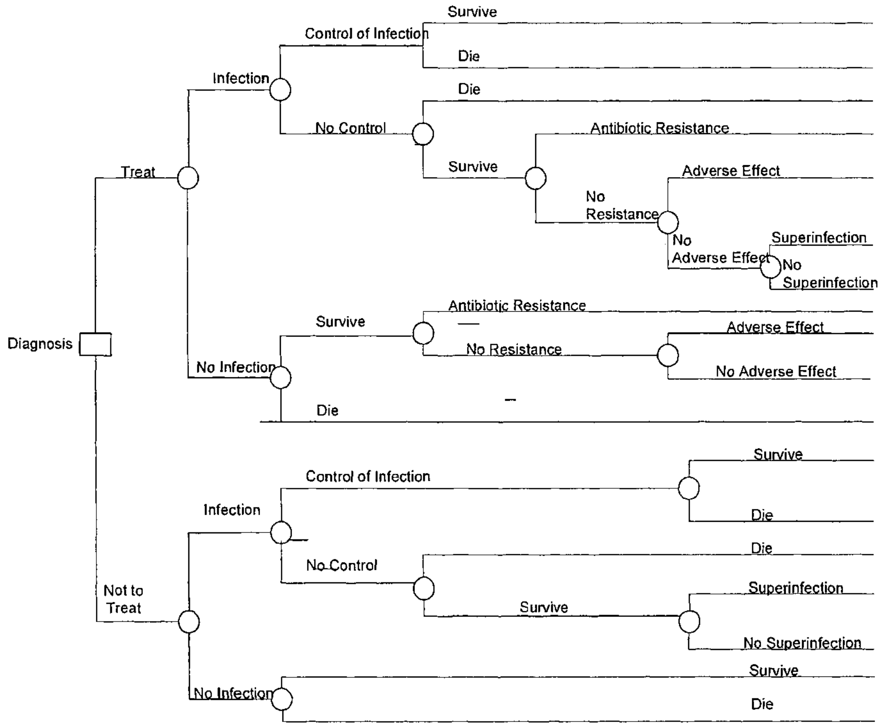

Figure 3: Decision tree for "treat with antibiotics" and "test first and treat with antibiotics after" strategies for the management VAP in critically ill

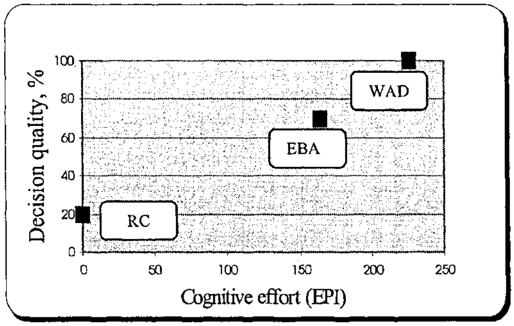

Figure 4: Effort and decision quality tradeoffs for prescribing decision strategies. The x-axis represents quality relative to the weighted-additive strategy (WAD) normative model. EBA, elimination by aspect strategy; RC, random choice strategy.

References

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Appendix

EIPs for WAD strategy are 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 32 tree branches to calculate to calculate path probabilities for each of 18 outcomes. Thus, the EIPs required for this stage are 5*32=160.
2. 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 32 tree branches to calculate to calculate path probabilities for each of 18 outcomes. Thus, the EIPs required for this stage are 5*32=160.
3. EIPs for computing expected utilities of the outcome: *retrieve* path probability and *retrieve* the utility for the outcome, *multiply* them, *store* the result. For 18 outcomes the score 18*4=72.
4. 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 160+72+11+7+4=254. With the decision support aid, only 17 EIPs (retrieving, comparing and eliminating utilities for 6 possible outcomes) are required.