Knowledge-Based Method for Building Patient Decision-Analytic Tools

Amar K. Das, MD, PhD[1], Bilal A. Ahmed[1], Yael Garten, MS[1], Jeremy I. Robin, MS[1], and Mary K. Goldstein, MD, MS[2,3]

[1]Stanford Medical Informatics, Stanford University, Stanford, CA 94305
[2]Geriatric Research, Education and Clinical Center, VA Palo Alto, Palo Alto, CA 94304
[3]Center for Primary Care and Outcomes Research, Stanford University, Stanford, CA 94305

Abstract

Numerous health decision aids (HDAs) have been developed to increase the participation of patients in shared decision-making, but many have limited accessibility and narrow applicability in clinical care. In the Health e-Decision project, we address these limitations in our work on building general HDAs targeted for older adults. Our approach uses a decision-support software architecture that enables principled methods for HDAs. We have formalized a novel knowledge-based decision model (KBDM), using Protégé OWL, that developers and clinicians can instantiate to tailor the components of the architecture for a particular health problem. In this paper, we present the methods used in the architecture and the knowledgebase design; the latter encompasses influence-diagram concepts, specific health problems, health outcome states, and probabilistic relationships. We discuss how this approach improves upon prior HDA methods. We also show that our use of computer-interpretable knowledge provides a structured, customizable means of enabling patient-centered decision support.

HEALTH DECISION AIDS

Health decision aids (HDAs), using formats ranging from written brochures to computer-driven multimedia programs, are designed to increase patient participation in health-related decision making by presenting information on reasonable options [1]. In addition, HDAs that are based on decision-analytic theory can help patients to determine relative values for possible outcomes of their healthcare choices based on measured preferences as well as their attitudes toward risk taking [2]. A review of randomized clinical trials of HDAs found that they could make patients better informed about medical conditions and the risk and benefits of management options [3]. Another review of HDAs found that patients generally rated their experience using them as positive [4]. Despite these benefits, HDAs are not routinely used in clinical care. Barriers to their widespread use include their stand-alone nature as software programs and the lack of time and resources in healthcare settings to use such programs [5].

Computer technologies, such as the Internet, can facilitate access to HDAs and allow their use at a time and place convenient for patients, not only as part of a rushed clinic visit [6]. Recent efforts to promulgate the use of secure Electronic Health Records (EHRs) also provide an opportunity to make HDAs readily available where EHRs allow patients to access their personal health information [7]. In the Health *e*-Decision project—funded by Stanford's Roybal Center on Advancing Decision Making in Aging—we are developing software methods to deliver HDAs through patient Web portals for EHRs.

One use case entails patients logging in to see their health record and accessing a provider-defined problem list with links to related HDAs. If a patient selects such a HDA, he or she can (1) review health education material and a decision model that communicates options and their health risks; (2) undergo preference assessment for possible health outcomes; and (3) be presented with information on which decision provides the maximal expected value (or, utility) based on patient-specific factors that are maintained in the EHR. The results of the HDA session can then be maintained in the EHR database. Providing the results later during a clinical visit offers a structured mechanism to facilitate physicians' awareness and use of patient preferences.

We argue that the ability to design and build HDAs in a standardized, yet flexible manner requires the use of computer-interpretable knowledge that formalizes the decision model, health problem, and patient-specific attributes. Such encoded knowledge has been successfully used in modern clinical decision-support architectures [8], and has been proposed for use in patient-oriented systems [9]. In this paper, we first illustrate the modeling challenges for building HDAs for a particular health problem. We next provide the software methods we employ for Health *e*-Decision and present our findings on defining and structuring a novel knowledge-based decision model (KBDM). The KBDM serves as the semantic foundation for our software architecture. We then discuss how the KBDM addresses the open challenges of making decision-modeling assumptions explicit, of tailoring the HDA to patient-specific factors, and of allowing reusability of the HDA.

EXAMPLE DECISION PROBLEM

There is ongoing debate about how involved patients want to be in making healthcare decisions. However, for 'decision-making' tasks, which involve selection among reasonable choices, many patients appear interested in playing an active role [10]. For older adults, such decision-making can entail complex choices that potentially lead to considerably better or worse functional health status.

In our initial work, we focus on the decision problem of atrial fibrillation, a common disorder among the elderly and one associated with a significantly increased risk of a thromboembolic stroke. Anticoagulation, which is most commonly accomplished with the medication warfarin, reduces the risk of stroke, but can cause catastrophic bleeding in the brain and abdomen, along with more frequent minor complications. Formal assessment of patient preferences for these outcomes can lead to clinical strategies that differ from guideline recommendations or physician practice [11]. For example, a study on the decision to use warfarin that incorporated patient preferences found that one-half of those who were not receiving warfarin would favor it, whereas one-half currently on warfarin would choose to be not taking the medication [12].

Man-Son-Hing and colleagues [11] undertook a review and analysis of eight distinct HDAs that have been developed for this particular decision problem. These HDAs used three different approaches: decision analysis, probability trade-off, and audiobooklet. The decision models vary in how choices were presented (warfarin vs. no treatment, with or without an option of aspirin); how risks were modeled (annual risk vs. five year risk); and what outcomes were described in assessing patient preferences ('functionally dependent' after stroke vs. 'mild' stroke severity).

Althoug each HDA development team noted specific reasons for modeling this health problem as they did, the HDA designs do not make explicit the modeling assumptions nor facilitate the ability to modify the decision model. The goal of our work is to define a generic, sound approach to HDA design that makes explicit use of encoded knowledge, which can allow them to be tailored to specific health decisions and to be reimplemented based on different modeling choices. These aims are consistent with efforts by the International Patient Decision Aids Standards (IPDAS) Collaboration (http://ipdas.ohri.ca/) to promote the systematic development of HDAs.

SOFTWARE METHODS

In our design of Health *e*-Decision, we use four general approaches: (1) a utility assessment method; (2) an influence-diagram method; (3) a component-based architecture; and (4) a knowledgebase.

Utility assessment: We use a previously developed and assessed utility elicitation program—called Functional Limitation and Independence Rating (FLAIR)—that is suitable for older adults and that can assess the values that they place on possible outcomes [13]. FLAIR uses functional status, as measured by dependencies in the Activities of Daily Living (ADLs) [14] as outcomes for preference assessment, since ADLs are an important aspect of quality of life for older adults and a strong predictor of health outcomes. The current implementation, FLAIR2, is a modular Web-based program that can work across different computer system platforms. We have adapted the FLAIR2 interface to elicit patient preferences for the possible outcomes of treatment in HDAs developed with Health *e*-Decision.

Decision model: To model the decision-analytic component of the HDA, we use an influence diagram, a compact graphical method mathematically equivalent to a decision-tree representation [15]. Like a decision tree, an influence diagram uses three types of nodes—decision, chance, and utility. Unlike a decision tree, it explicitly represents the probabilistic and deterministic relationships among these variables. We use Netica™, a commercially available Bayesian probabilistic engine, to specify an influence diagram for the atrial fibrillation HDA (shown in Figure 1) and to determine computationally what the maximal expected utility is based on a set of utility values, predefined probabilistic relationships, and patient-specific factors. Although influence diagrams and related Bayesian approaches are widely used for probabilistic modeling, these methods are not able to capture the semantic meaning of domain concepts related to nodes and relationships. Our knowledge-based approach addresses this critical limitation.

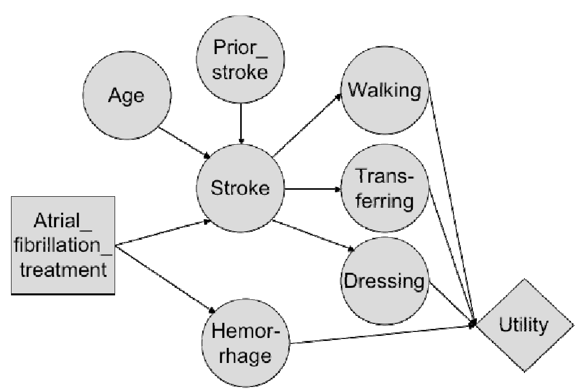

Figure 1. An example influence-diagram model of the decision to take warfarin following the onset of atrial fibrillation. The square indicates a decision node, the circles chance nodes, and the diamond a utility node.

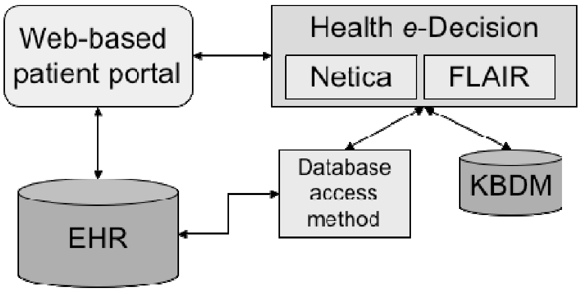

Figure 2. The software architecture of Health *e*-Decision. The KBDM is contained in an external OWL knowledgebase and encodes factors used to instantiate a HDA for a particular clinical decision, which is computationally implemented in Netica. The Health *e*-Decision program also supports a utility assessment tool (FLAIR) and accesses clinical data from an electronic health record database (EHR) to make the HDA patient specific. Patients interact with the system through a Web-based portal that allows the system to gather patient preferences and present the results of the decision model.

Software Architecture: Our research group has previously developed EON [16], a component-based architecture that can actuate decision support methods using data stored in EHR databases. The EON software architecture underlies the ATHENA decision-support system, currently deployed in outpatient VA settings to advise on hypertension treatment [8]. In Figure 2, we show the design of a similar software architecture approach for the integration of methods used for HDAs. The utility assessment and decision-model components within *Health e-Decision* are tailored to support particular health problems using the knowledgebase. They interact with the EHR in a run-time environment through a database-access program, and they provide access to encoded HDAs via the patient Web portal.

Knowledgebase: We use Protégé OWL (http://protege.stanford.edu)—the most-widely used knowledge-modeling environment for the Semantic Web ontology OWL—to formalize the KBDM for Health *e*-Decision. OWL ontologies (http://www.w3.org/TR/owl-features) can encode high-level descriptions and hierarchies of *classes* describing concepts in a particular domain and relating these classes to each other using *properties*. OWL can also represent data as instances of OWL classes—referred to as *individuals*—and provides mechanisms to reason with and manipulate those data. OWL also provides a powerful logic-based constraint language that defines precisely how concepts should be interpreted. Protégé permits easy modification of OWL classes and instances.

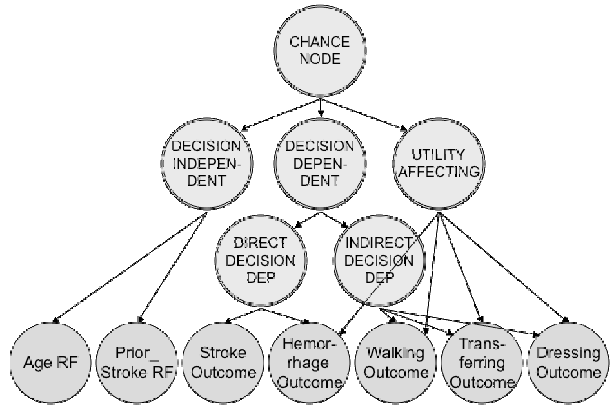

Figure 3. The KBDM classification of the structural roles of chance nodes in an influence diagram network. The lowest level corresponds to the chance nodes shown in Figure 1. An arrow indicates an is-a relationship. RF indicates a chance node representing a risk factor.

DESIGN RESULTS

We have created within Protégé OWL an ontology for the KBDM that structures the knowledge needed for the translation of a particular knowledgebase into a decision-analytic model in Netica. We report on the findings of our modeling work in this section.

KBDM Design: The KBDM encompasses the concepts used in creating a decision-analytic model of a particular health decision. The three main components of our ontology consist of (1) influence diagram concepts, (2) health problem concepts, and (3) health outcome concepts.

1. Influence diagram concepts: We model as upper-level OWL classes the concepts relevant to decision-analytic models and their structural interrelationships. We define as the main class NODE, which has subclasses of DECISION NODE, CHANCE NODE, and UTILITY NODE. Most decision-analytic model examples, whether influence diagrams or decision trees, start with a single decision node, by convention on the left, and end with a single type of utility node, on the right (as shown in Figure 1). Our KBDM correspondingly supports a DECISION NODE class and a UTILITY NODE class with no further subclasses related to their positional roles in a decision model.

Decision-analytic models typically have multiple chance nodes, which can have different roles in how a decision model is structured. We first classify all chance nodes as belonging to either DECISION INDEPENDENT or DECISION DEPENDENT classes. In Figure 1, the decision independent nodes are labeled Age and Prior_stroke, whereas the other nodes are decision dependent. The latter type can be further sub-classified into those that are linked directly to the decision node, called DIRECT DECISION DEPENDENT—such as the class labeled Stroke—and those that are not, called INDIRECT DECISION DEPENDENT—such as Walking. In addition, a chance node can be linked directly to the utility node; these chance nodes, such as Hemorrhage, belong to the subclass UTILITY AFFECTING. The KBDM representation of the structural classification of chance nodes in Figure 1 is shown by the hierarchy of Figure 3.

In addition to the hierarchy of structural roles that nodes have within a decision model, we also define OWL object properties for node classes. For example, decision dependent chance nodes have a property called HAS ASSOCIATED DICN to link them to decision independent chance nodes. HDA developers can use such OWL properties to structure a network of nodes from the decision node to a utility node. These properties are inherited by subclasses of each node class, including lower-level domain concepts categorized under types of chance node.

In defining the network structure of an influence diagram, we must also specify the probabilistic relationships between nodes. Based on previous work extending Bayesian modeling to OWL [17], we define a class called CONDITIONAL PROBABILITIES that is separate from the node class hierarchy. This upper-level class contains three properties—HAS VARIABLE, HAS CONDITIONS, and HAS PROBABILITY VALUE. In the Bayesian statement $P(x \mid y, z) = p$, the *variable* corresponds to x, the *conditions* y and z, and *probability value* p. We then define a property HAS CONDITIONAL PROBABILITY to relate each chance node to a set of conditional properties (a conditional probability table). We also define the HAS VALUE property to model the states of a chance node (such as whether a history of prior stroke is present or is absent). These properties allow HDA developers to encode directly a conditional probability for each value (or variable) of that node based on the values (or conditions) of influencing chance nodes.

2. Health problem concepts: We also use a domain model to relate clinical domain concepts semantically to influence diagram nodes and to constrain the meaning of a node in a decision model. For example, we represent the treatment Warfarin as a subclass of the general class DRUG TREATMENT and then use the HAS VALUE property to relate Warfarin to the Atrial_fibrillation_treatment subclass of DECISION NODE. Categories of clinical risk factors can be similarly mapped to subclasses of DECISION INDEPENDENT CHANCE NODE, such as the class labeled Prior_stroke RF shown in Figure 3. Using the KBDM, Developers and clinicians can define (and modify) a domain model and then relate those classes to influence diagram concepts to specify their modeling choices.

For HDA implementation, we also require a domain-related CONTEXT class, which is separate from the NODE class, to define when a particular decision model is relevant in clinical care. For example, the HDA for anticoagulation in atrial fibrillation is appropriate to present to a person receiving a new diagnosis of atrial fibrillation but not known to have a contraindication for the use of warfarin.

3. Health outcome concepts: Using our KBDM approach, we are able to formalize the relationship between health outcomes of decisions and the health states that are relevant to patient utilities. In using FLAIR within Health *e*-Decision, for example, we define a set of classes corresponding to ADL states (such as the need to dress with assistance) that can occur as a result of a stroke. We then ensure that relevant subclasses of UTILITY AFFECTING chance nodes, such as Dressing Outcome, are related to the states of the modeled health outcome.

The KBDM contains, in addition to the three main components presented here, classes and properties regarding patients and their demographic and disease factors. The KBDM also contains data-storage mappings to support the querying of patient-specific factors and clinical contexts stored within the EHR.

Automated Translation: We have developed a Java-based program that bridges the APIs of Protégé and Netica, reads in classes from the KBDM, and generates automatically a corresponding influence diagram in Netica. This program results in a problem- and patient-specific model for the HDA. To validate the expressivity of the KBDM, we have instantiated several decision models related to atrial fibrillation and validated the corresponding models visually in Netica.

DISCUSSION

Our research on the design of Health *e*-Decision has resulted in a novel knowledge-based method that supports the translation of decision science concepts into a standardized, yet customizable computer-based HDA technology. We have created an architecture to deliver this technology via a patient Web portal. Among the few studies incorporating HDAs into EHR systems is one by Ruland and Bakken [18]. They have developed a conceptual model for the development and implementation of HDAs using decision-support software for EHRs. Our work builds upon prior efforts by using formal knowledge representation methods to specify explicitly what HDA modeling choices are made.

A significant strength of our approach is the ability to change the specifications of a HDA design by editing the KBDM in Protégé OWL. Other HDA methods, in contrast, embed decision models within fixed code. Our knowledge-based method can also generate a HDA model that dynamically handles patient-specific health states and utility elicitation. For example, a patient whose EHR record indicates dependence for ambulation does not need to be presented with a utility assessment question related to the loss of walking independently. The KBDM requires formal knowledge-acquisition work to create HDAs, which is not needed when using other decision-modeling tools, such as Netica, alone. As groups such as IPDAS (http://ipdas.ohri.ca/) undertake coordinated efforts to design, implement, and disseminate HDAs, the benefits of standardization and reuse that our decision modeling approach provides may outweigh the costs incurred by knowledge engineering.

FUTURE DIRECTIONS

The next step in our work is to examine the usability of Health *e*-Decision via PAMFOnline, the Web portal for the patient EHR at the Palo Alto Medical Foundation. The long-term goal of our research is to evaluate the hypothesis that contextually rich clinical information, supported by formal decision models and available when needed in patient care, can lead to better health decisions by the elderly. We will make the OWL knowledgebase available upon request.

Acknowledgments

The authors thank Alan Garber, Martin O'Connor, Doug Owens, Daniel Rubin, Ravi Shankar, Tamara Sims, Paul Tang, and Samson Tu for their comments on this work. This work was supported in part by National Institute of Aging grants P30AG024957 and R01AG15110 and by National Library of Medicine training grant T15LM007033. Views expressed are those of the authors and not necessarily those of the Dept. of Veterans Affairs.

References

1. Barry MJ. Health decision aids to facilitate shared decision making in office practice. *Ann Intern Med*. 2002; 136(2):127-35.
2. Weinstein M, Fineberg H. *Clinical Decision Analysis*. Philadelphia: WB Saunders; 1980.
3. O'Connor AM, Rostom A, Fiset V, *et al*. Decision aids for patients facing health treatment or screening decisions: systematic review. *BMJ*. 1999; 319(7212):731-4.
4. Molenaar S, Sprangers MA, Postma-Schuit FC, *et al*. Feasibility and effects of decision aids. *Med Decis Making*. 2000; 20(1):112-27.
5. Holmes-Rovner M, Valade D, Orlowski C, *et al*. Implementing shared decision-making in routine practice: barriers and opportunities. *Health Expect*. 2000; 3(3):182-191.
6. Brennan PF, Strombom I. Improving health care by understanding patient preferences: the role of computer technology. *J Am Med Inform Assoc*. 1998; 5(3):257-62.
7. Cimino JJ, Patel VL, Kushniruk AW. The patient clinical information system (PatCIS): technical solutions for and experience with giving patients access to their electronic medical records. *Int J Med Inf*. 2002;68(1-3):113-27.
8. Goldstein MK, Coleman RW, Tu SW, *et al*. Translating research into practice: organizational issues in implementing automated decision support for hypertension in three medical centers. *J Am Med Inform Assoc*. 2004; 11(5):368-76.
9. Scott GC, Lenert LA. Extending contemporary decision support system designs to patient-oriented systems. *Proc AMIA Symp*. 1998:376-80.
10. Deber RB, Kraetschmer N, Irvine J. What role do patients wish to play in treatment decision making? *Arch Intern Med*. 1996; 156(13):1414-20.
11. Man-Son-Hing M, Gage BF, Montgomery AA, *et al*. Preference-based antithrombotic therapy in atrial fibrillation: implications for clinical decision making. *Med Decis Making*. 2005; 25(5):548-59.
12. Protheroe J, Fahey T, Montgomery AA, Peters TJ. The impact of patients' preferences on the treatment of atrial fibrillation: observational study of patient based decision analysis. *BMJ*. 2000; 320(7246):1380-4.
13. Sims TL, Garber AM, Miller DE, Mahlow PT, Bravata DM, Goldstein MK. Multimedia quality of life assessment: advances with FLAIR. *Proc AMIA Symp*. 2005:694-8.
14. Katz S, Akpom CA. 12. Index of ADL. *Med Care*. 1976;14(5 Suppl):116-8.
15. Nease RF Jr, Owens DK. Use of influence diagrams to structure medical decisions. *Med Decis Making*. 1997; 17(3):263-75.
16. Musen MA, Tu SW, Das AK, Shahar Y. EON: a component-based approach to automation of protocol-directed therapy. *J Am Med Inform Assoc*. 1996; 3(6):367-88.
17. Ding Z, Peng Y. A probabilistic extension to ontology language OWL. *Proc 37th Annual Hawaii International Conference on System Sciences*. 2004, pp. 111-20.
18. Ruland CM, Bakken S. Developing, implementing, and evaluating decision support systems for shared decision making in patient care: a conceptual model and case illustration. *J Biomed Inform*. 2002;35(5-6):313-21.