Expected Value Prioritization of Prompts and Reminders
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ABSTRACT

Computer-based prompting and reminder systems have been shown to be highly effective in increasing rates of preventive services delivery. However, there are many more recommended preventive services than can be practically included in a typical clinic visit. Therefore prioritization of preventive services prompts is necessary. We describe two approaches to prioritizing preventive services prompts based on expected value decision making. One method involves a static, global prioritization across all preventive services and has been used in a production system for almost 7 years. The second method uses influence diagrams to prioritize prompts dynamically, based on individual patient data. The latter approach is still under development. Both methods are labor intensive and require a combination of epidemiologic data and expert judgment. Compromises in strictly normative process were necessary to achieve user satisfaction.

INTRODUCTION

Computer systems that provide prompts and reminders to clinicians at the point of care are highly effective in improving rates of clinical services delivery, particularly for preventive services.[1] In fact, three critical reviews of the literature have emphasized the effectiveness of computer generated preventive services reminders. In 1994, Johnston identified 6 prospective controlled studies of the effect of computer-based decision support systems on the clinician performance. She found that 4 of 6 studies documented improvements.[2] In 1998, Hunt found 19 controlled trials of computer-based preventive services decision support systems of which 14 (74%) improved the process of care.[3] In 1999, Shiffman found similar results.[4]

For this reason it is tempting to incorporate a full range of preventive services in a clinical prompting and reminder system. Unfortunately, the number of preventive services recommended by authoritative bodies such as the US Preventive Services Task Force[5] exceeds what can be done in a typical clinic visit.[6] This is especially true for pediatrics in which there are typically only a few seconds for preventive care.[7]

To make the most efficient use of the time available for preventive care and to be acceptable in busy clinical environments, prompting systems should, ideally, prioritize preventive services prompts to maximize the benefit to patients. Expected value decision making [8] provides an attractive model for doing this prioritization. Expected value decision making involves ranking alternatives (e.g., candidate preventive services) by the expected value of their outcomes, where outcomes are valued by some objective function such as utility, cost, or life expectancy. Alternatives that maximize expected value would receive the highest priority.

We used expected value as a strategy for prioritizing prompts in a pediatric preventive services tracking and reminder system developed and implemented in the pediatric clinics at the University of North Carolina in Chapel Hill. In this paper, we describe a static prioritization approach that was has been in use since the system was installed in 1995 and a newer, experimental design, using influence diagrams.

METHODS

The Child Health Improvement Program: The Child Health Improvement Program (CHIP) is a computer-based preventive services tracking and reminder system that has been in clinical use in the resident teaching clinics at the University of North Carolina since 1995, and in a private practice in Raleigh, NC since 1996.

CHIP generates patient specific evidence-based reminders to health care providers to perform important preventive services at all clinic visits. The reminders are printed on a worksheet that the clinician uses during the clinic visit. At the end of the visit, a scanning mechanism automatically captures data recorded on the worksheet, adding it to the patient’s computerized database without the need for data entry personnel. CHIP consists of four components that work together to improve preventive care:
1) A guideline database: CHIP includes a guideline database that contains a complete preventive services program for young children in the form of computerized guidelines. The guidelines are represented as approximately 200 reminders that may be printed for the clinician.

2) A patient database: A computer-based patient database stores demographic information on each child and tracks problems, risk factors, and services the child has received. This database represents a partial electronic medical record, containing clinical data regarding preventive services that are captured during routine use of the system.

3) A provider worksheet (PWS): When a child arrives in the clinic or office, CHIP compares the patient’s clinical data to the guideline database to select the preventive services that this particular child needs. For one child, this may mean catching up on late immunizations, for another, reminding parents of the importance of car seat use, for yet another, giving the parent suggestions on how to stop smoking. CHIP assembles the highest priority preventive services into a printed worksheet that providers use as the medical record for the visit. The worksheet has a prompt and check box format (figure 1). The prompts remind providers of preventive services, but may also include information for the provider and the parent, such as risks associated with environmental tobacco smoke or instructions on correct car seat use. The check boxes allow the provider to document, quickly and easily, the data collected and the services provided.

4) A worksheet scanning module: The health care provider uses the worksheet during the patient visit. At the end of the visit, the worksheet is fed into a document scanner. The scanner reads the check boxes and updates the patient’s clinical database. This allows the system to track preventive services and generate more appropriate and relevant prompts at the child’s next visit.

The Need for Prioritization: CHIP prints eight prompts on each worksheet. However, at any given visit, the child is typically eligible for many more preventive services. In order to assure that the most important preventive services are addressed first, we developed two strategies for using expected value to select prompts and reminders. The first, a static prioritization, has been used in the Child Health Improvement Program since its implementation in 1995. The second, a dynamic prioritization, using influence diagrams to tailor the prioritization to the individual patient, is being developed for a new version of the system.

![Figure 1: The Provider Worksheet (PWS)](image)

**Static Prioritization:** To prioritize the prompts, we reviewed published literature and federal and state statistics to determine the burden of suffering from preventable conditions and the potential efficacy of physician-based prevention strategies. Burden of suffering was defined as the combination of mortality and hospitalizations attributable to the preventable condition or event. We prioritized the strategies in a decision analytic framework by taking the product of the strategy’s potential efficacy and the burden of suffering from the condition it prevents. This raw number was normalized to a scale from 0 to 100. The scale was used as the basis for prioritizing prompts to be printed on the provider worksheet. Every prompt in the database was associated with a priority score based on this scale. No two prompts received the same score.

This scoring system gives higher priority to problems that are prevalent, high risk or for which an intervention is likely to be effective. Prompts for which the risk of a problem was high include breast feeding advice to a mother who had reported breast feeding. A prompt for which the intervention is highly effective would be automobile safety seat use.
The CHIP algorithm identified all of the preventive services a child was eligible to receive at a given visit, and selected the eight with the highest priority scores. Thus, prevention strategies were prioritized by the overall impact they would be expected to have on morbidity and mortality.[9]

Unfortunately, morbidity and mortality data on preventable conditions and data on the efficacy of preventive strategies are often not available. Therefore, ad hoc prioritization, based on recommendations of authoritative bodies such as the American Academy of Pediatrics or the clinical judgment of the development team, was used for many of the prompts. As an additional strategy for prioritization, and as a validation of our approach, we conducted a modified Delphi consensus process with expert pediatricians nationally. This work is described elsewhere.[10]

This global, static prioritization strategy is also limited in that it does not change priorities based on an individual patient’s circumstances. The presence of risk factors, for example, might make one screening or prevention strategy more or less important than another in a particular patient. We sought to develop an expected value strategy that could prioritize dynamically, based on an individual patient’s status at a given point in time.

Dynamic Prioritization with Influence Diagrams:
An influence diagram is an acyclic directed graph that represents the conditional dependencies among random variables, alternative strategies, and values of outcomes.[11] We use influence diagrams as a statistical representation of the clinical problem that the preventive guideline addresses. Figure 2 shows a portion of an influence diagram. The round “nodes” represent clinical states (lead intoxication and iron deficiency), risk factors for these states, and test results (hematocrit and blood lead). Arrows between the nodes represent causal or probabilistic relationships between these variables. Associated with each of the variables are the values it can take on. For example, the hematocrit may be high or low. The likelihood the variable will take on a specific value depends on the values of the other nodes that have arrows pointed into it. For example, the influence diagram in the figure stores the information that 20% of children with a history of an iron poor diet (a risk factor for anemia) will have iron deficiency and that there is an 80% probability of discovering anemia on a screening hematocrit in a child with iron deficiency.

With this information, the computer is able to assess the probability of any particular state of affairs for an individual patient. For example, the physician may assess a patient’s risk factors for lead exposure and determine that they are negative. At that point the system determines that the risk of elevated lead level is sufficiently low that a blood lead test is not indicated. Next the physician determines that the diet is deficient in iron and, therefore, the computer finds that the risk of iron deficiency is sufficient to justify a hematocrit test. If the result of the hematocrit test is low (i.e., there is anemia), the computer can back-calculate that there is an increased risk of iron deficiency. Moreover, because iron deficiency increases the risk of elevated lead level, the computer now determines that the risk of an elevated lead level is sufficient to justify obtaining a blood lead test.

The CHIP system is being re-implemented using an influence diagram architecture. The system determines which variables the physician needs to assess based on each variable’s expected value information, the average improvement in patient outcome that would be expected by knowing the information. The system selects actions to recommend to the physician based on their expected value. Patient outcomes will be quantified by cost-utility analysis. Total costs associated with providing, or not providing, a preventive service will be explicitly modeled, as will patient utilities. The influence diagrams will be analyzed with the objective of optimizing the incremental cost-utility ratio.

Machine Learning: The influence diagram representation also provides a way for the computer
to "learn" from the data it receives. The nodes of the influence diagram store the probabilistic relationships between risk factors, health states, diagnostic tests and other clinical variables. These probabilities represent prevalence, sensitivity, specificity and other statistical concepts. Key, poorly known variables can be stored as probability distributions (best estimates with a range of possible values). For example, the probability a low hematocrit, $p$ among patients with iron deficient diets, may be estimated at 20%, but that estimate will be recorded as a probability distribution, $f(p)$ with mean of 20% and a standard deviation of 12%. When the value of a particular hematocrit is known, the computer can use the result to adjust the probability distribution, using Bayes' theorem, (1) below. Using the probability of a low hematocrit, given each possible value of $p$, $p(H|p)$, each time the computer "sees" a low hematocrit, it updates the distribution for the probability of a low hematocrit using Bayes' theorem (1).

$$f(p \mid H) = \frac{p(H \mid p) \cdot f(p)}{\int_{0}^{1} p(H \mid p) \cdot f(p)}$$ (1)

Since the probability of seeing a low hematocrit given any particular value of $p$ is simply $p$, equation (1) reduces to:

$$f(p \mid H) = \frac{p \cdot f(p)}{\int_{0}^{1} p \cdot f(p)}$$ (2)

where $f(p)$ is any probability distribution function over the possible values of $p$. In this way, with "experience", the computer adjusts itself to local variations or inaccurate initial assumptions.

We are using the Netica software package (Norsys Software Corp., Vancouver, BC, Canada) to represent and train influence diagrams.

**RESULTS**

**Static Prioritization:** In a survey of residents, attendings and nurse practitioners using CHIP, 90% said they usually or always used the system for well child check, and all said that the system reminded them to ask or do things they would otherwise have forgotten. Overall, 85% had a favorable rating of the system.

However, when CHIP was first introduced into clinical practice, providers complained that certain, standard preventive health issues were not appearing predictably on the worksheets. Examples of these topics include sleep patterns and certain dietary topics. These topics had insufficient priority ratings to appear on the initial worksheets. However, they were viewed by users as an indispensable part of the well child visit. In order to improve user satisfaction and insure use of the system, we "artificially" raised the priorities of these topics.

**Dynamic Prioritization:** The algorithms for prioritizing prompts with influence diagrams are still under development. So far, eight networks have been developed, covering the following topics: developmental delay, safety counseling, health behavior counseling, screening for hearing impairment, screening for lead intoxication, screening for tuberculosis, nutritional counseling and screening, and risk assessment for domestic violence. Together, these diagrams represent 164 nodes, 174 arcs, and 1052 conditional probabilities. As with the static prioritization procedure, many of these values are not available in the literature. However, we have been able to train the influence diagrams using algorithms provided by the Netica software package and the data in the CHIP database.

**DISCUSSION**

The combination of a vast number of clinical care guidelines and the tight time constraints inherent in most clinical setting makes prioritization of guidelines essential. This results not only from the lack of time clinicians have to respond to multiple prompts, but their tendency to begin to ignore prompts and reminders when they receive too many of them.

We have had success in developing a fairly simple model for prioritizing prompts based on expected value decision making. Ironically, the primary objection we received from providers was that the prompts selected based on maximum expected value did not include certain preventive services topics they considered part and parcel of pediatric preventive care. We adapted the system for the sake of user acceptance, at the expense of giving up a prioritization based purely on expected value. This begs the question of whether evidence based care will be compromised for the sake of user acceptance as much as computer-based decision support systems will improve evidence-based practice.

The complexity that is introduced when using an explicit approach, such as expected value decision making, points out the inadequacies of the data
needed to prioritize services objectively. Indeed, expert judgment is absolutely necessary to fill in the gaps in our knowledge of the epidemiology of disease and effectiveness of our interventions. Happily, decision modeling provides a convenient strategy to marry subjective probability estimates with available data. Furthermore, the Bayesian techniques exploited in this project make it possible to incorporate data that are routinely collected as the system is used.

Although the current model for the CHIP system involves printing prompts on a scannable paper worksheet, the influence diagram model creates interesting possibilities for real-time prioritization as data are entered. Calculations on the influence diagram would be carried out “in the background”. A computer interface, which allows the physician to interact with the system using a hand, held computer and a format similar to the paper version in CHIP could prioritize “on the fly.” The physician might, for example, first see a prompt to assess whether the patient has risk factors for lead exposure. After indicating that these are negative, the physician sees the prompt to assess the diet for iron content. When the physician indicates that the diet is iron deficient, the system responds with a prompt to determine the hematocrit. When the abnormal results of the hematocrit are entered, the system responds with a prompt to obtain a blood lead test (along with an explanation of the risk factors justifying it). Embedding the influence diagram in the computer would allow the computer to respond immediately to the data entered by the physician, customizing the prompts to the status of the patient as it is assessed.

REFERENCES


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