Model Formulation ■

Representation of Clinical Practice Guidelines in Conventional and Augmented Decision Tables

RICHARD N. SHIFFMAN, MD, MCIS

Abstract **Objective:** To develop a knowledge representation model for clinical practice guidelines that is linguistically adequate, comprehensible, reusable, and maintainable.

Design: Decision tables provide the basic framework for the proposed knowledge representation model. Guideline logic is represented as rules in conventional decision tables. These tables are augmented by layers where collateral information is recorded in slots beneath the logic.

Results: Decision tables organize rules into cohesive rule sets wherein complex logic is clarified. Decision table rule sets may be verified to assure completeness and consistency. Optimization and display of rule sets as sequential decision trees may enhance the comprehensibility of the logic. The modularity of the rule formats may facilitate maintenance. The augmentation layers provide links to descriptive language, information sources, decision variable characteristics, costs and expected values of policies, and evidence sources and quality.

Conclusion: Augmented decision tables can serve as a unifying knowledge representation for developers and implementers of clinical practice guidelines.

■ **J Am Med Inform Assoc.** 1997;4:382–393.

Soaring costs of health care and the recognition of widespread variations in clinical practice have brought about a major health policy initiative dedicated to the development and implementation of clinical practice guidelines. Guidelines are intended to direct medical care toward clinically appropriate and cost-effective interventions, which are based on the best scientific evidence available. The informatics community has been challenged to support the transition to evidence-based medicine by helping to create the technologies necessary to make practice guidelines more accessible, manageable and updatable.[1,2]

Affiliation of the author: Center for Medical Informatics and the Department of Pediatrics, Yale School of Medicine, New Haven, CT.

This work was supported in part by the National Library of Medicine through grant 1-R55-LM 05552-01A1. Dr. Shiffman is a Robert Wood Johnson Generalist Physician Faculty Scholar.

Correspondence and reprints: Richard N. Shiffman, MD, Center for Medical Informatics, TMP-3, PO Box 208009, New Haven, CT 06520-8009. E-mail: richard_shiffman@qm.yale.edu

Received for publication: 1/11/97; accepted for publication: 4/29/97.

From an information management perspective, a clinical practice guideline can be viewed as a knowledge base: i.e., a set of statements elicited from experts that describes a circumscribed domain. Knowledge acquisition techniques that have proven useful to knowledge engineers in the formalization, verification, and optimization of knowledge bases also can be applied productively to the development, implementation, and evaluation of practice guidelines.

A critical activity in the knowledge modeling process is the selection of a mediating representation. The appropriate choice should be right for the domain (for the kinds of knowledge to be represented), right for the task (for what needs to be done with the knowledge), and right for the user (human or machine).[3]

A knowledge representation for clinical practice guidelines must be adequate to express the complexities and nuances of clinical medicine as expressed in guideline statements. An appropriate choice should match the domain experts' normal problem-solving language and allow the experts to transform their knowledge into an effective model with little effort. Likewise, the model should be comprehensible to its target audience. Guideline developers recognize four phases of the guideline life cycle—development, dissemination, implementation, and revision. Ideally, a guideline knowledge model should be reusable in each phase to mitigate the adverse effects of repeated translation. Finally, since medical knowledge is constantly changing, the model must be capable of being maintained and updated. This paper will describe a guideline knowledge representation model based on decision tables that meets each of these criteria. In addition, a model that enhances the expressivity of the conventional table—the *augmented* decision table—will be defined.

Current Systems for Guideline Knowledge Representation

Before publication, the relevant knowledge that defines a clinical practice guideline is assembled from literature review, meta-analysis, decision analytic modeling, and expert consensus. The information is entered into evidence tables (which describe evidence sources and quality,[4] balance sheets (which describe benefits, risks and harms of various strategies,[5] and annotated algorithms.[6] Guideline development committees most commonly operationalize this information as paper-based, prose documents, which may be accompanied by algorithmic flowcharts. Following dissemination, guideline implementers must translate the recommendations into a medium that will influence the decision-making of practitioners. Grimshaw and Russell showed that the highest probability of an effective guideline implementation occurs when patient-specific advice is provided at the time and place of a consultation.[7]

Tierney et al. enumerated the difficulties of implementing an evidence-based guideline for management of congestive heart failure in a computer-based format.[8] They found that the guideline developers had failed to explicitly define the algorithm's branch points and the guideline lacked a clear definition of states and modifiers. Fifteen of sixteen specified actions had to be modified. They recommend that all guideline recommendations should be written in a simple if-then-else format with all of the parameters strictly defined using routinely collected clinical data.

The Arden Syntax has been recognized as a standard representation of medical knowledge for decision making and a means by which that knowledge can be shared.[9] Using Arden, clinical decisions are atomized into individual Medical Logic Modules (MLM), which can be implemented as alerts and reminders and shared inter-institutionally.[10] Unfortunately, MLMs have a limited capability to express the complex interacting recommendations of guideline statements. Sherman and colleagues addressed the inability of Arden to deal with interacting rules by defining intermediate states that exist outside of the MLMs, which can be stored in a database and used to trigger subsequent decisions.[11]

Several knowledge models have been used for implementation of guideline knowledge. To encode a cholesterol guideline, Starren and Xie compared a first order logic-based system, a frame-based representation system, and a production rule system.[12] They found that although all three were adequate, the production rule system was easiest to use to conceptualize and formalize the guideline knowledge. GEODE-CM uses a state-transition model to encode logic for diagnostic workups.[13] Patient-specific information is collected in the context of a "clinical management state" to enable physicians to focus on task-specific data and to be provided with relevant reminders and guidelines. The EON architecture is an elaborate model for representing treatment protocols that has been applied to automation of protocol-based care related to AIDS and breast cancer.[14] Episodic skeletal plan refinement is used as a problem-solving method in combination with a temporal query system to instantiate a detailed plan for a given patient. The ASGAARD Project seeks to represent guidelines and the underlying intentions in a standard, machine- and human-readable format.[15] However, none of these models has attempted to represent guideline knowledge throughout the entire guideline life cycle.

Shiffman and Greenes described a method for translating guideline knowledge into decision table-based rule sets.[16] These rule sets can be used effectively during guideline development, implementation, and revision.

Effective Guideline Knowledge Representation

The key knowledge contained in a clinical practice guideline is a set of one or more recommendations for care. These recommendations are the salient features that distinguish a guideline from a literature review; the intent of guidelines is to influence clinical practice—not simply to describe the state of the art.[17]

Typically there is much supporting verbiage that describes the background clinical issues, the methodology of guideline development, and the evidence supporting guideline statements; however, the thrust of a guideline can be distilled into a series of situation-action statements. *If* the antecedent circumstances exist, *then* one should perform the recommended actions.

A rule-based model seems natural for formalization of guideline knowledge. Rules are simple conditional declarations that link a logical combination of antecedent conditions to a set of consequents. Rules have been used successfully to represent expert knowledge in medicine and other fields. Rules can easily represent the following four general types of guideline statement:

Situation/action: This fundamental conditional covers most therapeutic guideline recommendations. Given a set of clinical conditions, the following action(s) are recommended, e.g.:

IF Within 31 days of an acute myocardial infarction
In a patient with coronary artery disease involving the left main coronary artery
Whose ejection fraction is >35%
AND whose surgical risk is low (i.e., Parsonnet Score <9)
THEN coronary artery bypass graft is appropriate.[18]

Premise/conclusion: This statement is useful for diagnostic guidelines and for determination of eligibility. Given the listed circumstances, the conclusion is valid, e.g.:

IF the patient has otitis media with effusion
AND age is 1–3 years
AND there are no craniofacial or neurologic defects
AND there are no sensory deficits
THEN the patient is eligible for guideline advice.[19]

Sufficiency: The listed circumstance(s) are sufficient to justify the consequent clause, although other circumstances might result in the same conclusion.

IF the pregnancy was complicated by intravenous drug abuse
THEN consider the newborn to be at high risk for hepatitis B infection (although clinically apparent hepatitis or sexually transmitted disease during the pregnancy would likewise put the child in a high-risk category).[20]

Definition: The antecedent conditions define the meaning of the consequent clause:

IF seizure is generalized
AND is accompanied by fever
AND occurs without CNS infection
AND occurs in a child between 6 months and 5 years of age
AND seizure duration is less than 15 minutes
AND seizures do not recur within 24 hours
THEN this is a *simple febrile seizure*.[21]

Several advantages accrue to guideline developers, implementers, and users who represent guideline knowledge in this manner. The process of reducing guidelines to a set of rules forces developers to examine their recommendations from a fresh perspective. The process often identifies unclear or ambiguous decision variables or actions.

Additionally, guidelines can be formally verified when guideline recommendations are represented as rules. Verification refers to establishment of the internal correctness of a system, i.e., the absence of such logical flaws as incompleteness and ambiguity.[16,22] Current methodologies used by guideline developers do not include verification methods.[23]

Rules provide a mechanism for encapsulating individual chunks of knowledge, thus facilitating maintainability. This modularity permits adding and subtracting statements without interfering with the basic organization of a knowledge base or guideline.

Rules can also facilitate explanation: by linking decision variables with actions the reasoning that supports a recommendation is declared, thereby enhancing a user's confidence in the recommendation.

Importantly, restatement of guideline prose as IF . . . THEN statements simplifies the task of guideline implementers.[8] Any Turing-complete programming language can encode conditional statements enabling the use of a variety of implementation techniques.

It seems natural and reasonable to expect that guideline recommendations either would appear as rules or could be readily translated into an *IF . . . THEN* structure. Yet many current guidelines are presented either as bodies of evidence followed by a list of imperatives or as flowcharts isolated from any supporting context.

Conventional Decision Tables for Guideline Knowledge Representation

Decision tables can be used to display, verify, and optimize guideline knowledge as logically cohesive sets of rules. Decision table theory is rigorously grounded in mathematics and logic[24,25]; nonetheless, decision tables can provide a simple tabular representation of complex decision logic.[26] A rule set represented in decision table form can be readily checked to assure comprehensiveness and the absence of redundancy and contradiction.[27–30] Methods for converting decision tables into optimized sequential testing procedures have been successfully developed and refined.[31–33] Optimized rule sets can be implemented in any rule processing shell or can be executed directly by a decision table execution program.[34,35]

Decision tables have been used by computer programmers and systems analysts to confirm completeness and identify ambiguity in rule sets for over thirty years. Vanthienen and coworkers have applied decision tables productively for knowledge acquisition in law, business, and other domains.[36–38]

In spite of their ability to organize and clarify complex logic, decision tables have not been applied widely in medicine. Medical uses for decision tables were first described in 1975 with Holland's suggestion that they be used as an alternative to flowcharts to facilitate medical care.[39] Since then, decision tables have been used sporadically as tools to elucidate the medical decision-making process, especially for educational purposes.[40–43] Schwarz and co-workers used decision tables to construct a decision support system for management of liver metastases and found that use of this knowledge representation facilitated the knowledge acquisition process.[44]

Glasziou and Hilden used a modified decision table to devise a minimum-cost testing sequence and found their technique to be more efficient than standard decision tree approaches.[45,46] Glasziou has suggested that decision tables be used as an integral part of the guideline development process rather than as a post-policy check.[47]

Decision Table Display

A decision table is a matrix that associates a set of decision variables with a set of actions. In medicine, decision variables include patients' symptoms, physical examination findings, and the results of laboratory tests. Actions include initiating a treatment, undertaking a risky or expensive diagnostic evaluation, or concluding a diagnosis. In a decision table, each decision value is represented as a categorical value (e.g., diabetes is present or absent) or as a range of a continuous variable (e.g., cholesterol >270 mg/dl). The number of values that each decision variable can assume is defined as the *modulus* of the decision variable.

The conventional display of a decision table lists the decision variables (or *conditions*) in the upper left quadrant called the *condition stub* and lists the names of the relevant actions in the lower left quadrant termed the *action stub* (Fig. 1a). The *condition entry quadrant* at the upper right lists the values or states of the decision variables and the *action entry quadrant* at the lower right indicates the appropriate actions given the pertinent combination of decision values above. Each column in the entry area is a rule, whose antecedents are derived from the condition entries and whose consequents are indicated by the action entries below them.

In some circumstances, the value of a particular decision variable is irrelevant to the satisfaction of a rule. For example, in deciding whether to treat a patient who has sore throat, cervical adenopathy, and a positive throat culture, the presence or absence of adenopathy is immaterial, although it may be an important consideration if the throat culture result is unknown. Such irrelevant decision values are represented as dashes in the table.

Assuring Complete Rule Sets and Finding Missing Rules

A rule set is said to be complete when all mathematically possible combinations of conditions have been accounted for: i.e., when every combination of decision values has been considered. One can determine

(a)

Condition Stub | Condition Entries

	Mod	1	2	3	4	5	6	7
Symptom	2	Present	Present	Present	Present	Absent	Absent	Absent
Physical Finding	2	Present	Present	Absent	Absent	Present	Absent	Absent
Lab Result	2	Positive	Negative	Positive	Negative	—	Positive	Negative
Treatment 1		X		X		X		X
Treatment 2			X		X		X	

Action Stub | Action Entries

(b)

		Column Count						
Π Moduli	8							
Σ Column Counts	8	1	1	1	1	2	1	1

Figure 1 Conventional representation (a) of a four-quadrant decision table. Each column is a rule so column 3 may be read: IF Symptom is Present AND Physical finding is Absent AND Lab Result is Positive THEN Perform Treatment 1. Determination (b) of the completeness of a decision table rule set. The product of the moduli—eight—equals the sum of the column counts and all combinations of decision variables are unique.

that a rule set is complete by comparing the number of rules displayed with the product of the moduli of all the decision variables. If the number of unique rules equals the product of the moduli, then every combination of conditions has been accounted for. If the number of rules is less than the product, then some combination of conditions is not included and the rule set is not comprehensive. (The number of rules can only exceed the product of the moduli when there is ambiguity in the rule set, since some combination of values must be represented more than once.)

Each column that contains dash entries is called a *complex rule.* A complex rule actually represents a number of rules since each dashed value could be replaced by any value of the dashed condition. The *column count* of a complex rule indicates the number of rules represented and is calculated as the product of the moduli of all the dash entries in the column. For a simple rule, the column count is 1. To determine the completeness of a table with complex rules, the product of the moduli of the decision variables must equal the sum of the column counts of all the rules (Fig. 1b).

It is possible to identify which rules are missing from an incomplete rule set. An exhaustively enumerated set of decision value combinations can be created by displaying the Cartesian product of all the decision values. Each column in this set is compared with the incomplete rule set and identical rules are "checked off." Any remaining decision value combinations are missing.

Ensuring Consistency of Rule Sets

Rule set development and maintenance may create situations where inconsistencies are introduced into a knowledge base. The consistency of a rule set can be assured by verifying that each column of decision values is unique. If two or more columns contain the same decision values, then the rule set is ambiguous. Ambiguity includes three possible situations: The rule set is said to be *redundant* if two or more columns are exactly the same. If two or more sets of decision values are the same, but the actions called for are different, the rule set is said to be *contradictory.* And if two or more non-unique condition sets call for action sets that overlap, the rule set is said to be in *conflict.*

Consolidation and Decomposition of Decision Table Rule Sets

Techniques have been developed to consolidate and effectively display large rule sets to make them more comprehensible to users. The number of rules required to completely characterize a domain can be reduced by elimination of any rules that involve testing of irrelevant variables. To find candidate rules for elimination, a decision table is examined to identify rules that call for the same action(s) and differ at only one decision variable. If the modulus of the variant condition is two (i.e., the test outcome is binary), then the two rules are identical except that one contains the irrelevant value and the other contains its negation. We know the decision variable must be irrelevant to the satisfaction of this rule since either its presence or absence results in the same action. One of the rules may be eliminated from the table and the remaining rule should have a dash inserted in the entry for the variant condition. The dash indicates the irrelevance of the variant condition to the satisfaction of the rule. When the modulus of the variant condition is greater than two, the number of rules indicated by the modulus must be combined.

Hurley has described a method for decomposition of a decision table that allows it to be transformed into a more easily understood and manipulated decision tree (Fig. 2).[30] The transformation requires sorting both the rows and columns of the table. The *weighted dash count* (WDC) serves as a primary key for sorting the decision table's condition rows. The WDC of a decision variable is a measure of the irrelevance of that condition to decision-making. The WDC is calculated for each row by adding the column counts of all the columns whose entries in that row contain dashes.

If the WDCs of two or more rows are identical, the row DELTA can be used as a secondary sorting key. Like the WDC, the DELTA is inversely related to the quality of the decision variable as a discriminator in the rule set. The DELTA is calculated for each row by counting the number of entries for each explicit (non-dash) value in the row. The DELTA is the absolute value of the difference between the highest count and the sum of all the other counts (Fig. 2b). For example, in row 1 for the Age decision variable, there is 1 entry for each of the age values ("<12 m", "12–18 m", and ">18 m"). The highest count is 1 and the sum of all the other explicit counts is 2. The absolute value of the difference (i.e., $|1 - 2|$) gives a DELTA of 1.

The first step in decomposition is to sort the rows so that those with the lowest WDCs are in the topmost positions in the table (Fig. 2c). In the case of identical row WDCs, the delta is used as a secondary key to sort the rows in ascending order.

After the rows have been sorted, the columns are rearranged so that all rules that contain the same condition entry value for row 1 are brought together. Next, all the columns that share the same value for

(a)

Age	<12 m	<12 m	<12 m	<12 m	12–18 m	12–18m	12–18 m	12–18 m	>18 m	>18 m	>18 m	>18 m
Meningeal signs	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Prior antibiotics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Lumbar Puncture	Str	Str	Rec	Rec	Cons	Str	Rec	Rec	NR	Str	Rec	Rec

(b)

	Mod						*WDC*	*Delta*
Age	3	—	<12m	—	12–18 m	>18 m	9	1
Meningeal signs	2	Yes	No	No	No	No	0	3
Prior antibiotics	2	—	No	Yes	No	No	6	2
Lumbar Puncture		Rec	Str	Str	Cons	NR		
Π Moduli	12							
Σ *Column Count*	*12*	6	1	3	1	1		

(c)

	Mod						*WDC*
Meningeal signs	2	Yes	No	No	No	No	0
Prior antibiotics	2	–	No	Yes	No	No	6
Age	3	—	<12m	—	12-18m	>18m	9
Lumbar Puncture		Rec	Str	Str	Cons	NR	

(d)

	Mod					
Meningeal signs	2	Yes	No	No	No	No
Prior antibiotics	2	–	Yes	No	No	No
Age	3	—	—	<12m	12-18m	>18m
Lumbar Puncture		Rec	Str	Str	Cons	NR

(e)

Meningeal signs	2	Yes	No			
Prior antibiotics	2	–	Yes	No		
Age	3	—	—	<12m	12-18m	>18m
Lumbar Puncture		Rec	Str	Str	Cons	NR

Figure 2 Reduction and decomposition of a guideline rule set that provides recommendations for lumbar puncture (LP) in children with suspected febrile seizures.[21] The exhaustively enumerated set is shown (a). Note that the product of the moduli equals the sum of the column counts. Language from the guideline is shown. Rec: recommended; Str: strongly consider; Cons: consider; NR: not recommended. The original 12-rule set (b) is reduced to an equivalent table of 5 columns. Weighted dash count (WDC) and Delta values are shown for each row. The table is row-sorted (c) in order of ascending WDC. Column sort (d). Beginning in the top row, like-valued cells are brought into adjacent positions hierarchically. Adjacent, like-valued cells (e) are merged to create a decision tree.

condition 1 are sorted to bring together those with the same value of condition 2 (Fig. 2d). The procedure is continued until all the rows have been visited. This sort leaves the columns arranged in an order that is equivalent to a decision tree (Fig. 2e). In this tree, each node is equivalent to the row stub and the branches represent the decision values (Fig. 3).

Dealing with Knowledge Complexity

Although a mathematically complete rule set comprehensively describes the domain covered by the conditions, it may be unwieldy since the rule set grows combinatorially with each condition added. Automated decision table processing tools can deal with large numbers of rules, but human comprehension of the content is diminished with increasing size of the rule set.

Several techniques have been applied to deal with large numbers of rules in decision table rule sets. Conventional consolidation can dramatically improve the comprehensibility of the rule set as described above.

The exhaustive enumeration of rule sets based on all possible values of decision variables frequently includes large numbers of rules that are either illogical in all possible worlds (e.g., the combination of male gender and pregnant) or are impossible because of particular assumptions of this guideline. For example, in a CDC hepatitis immunization guideline, a patient who tests positive on one occasion is treated as being infected; there is no consideration of a false-positive.[20] Explicitly declaring these assumptions makes them available for review, clarification and modification. Elimination of all rules that violate these basic assumptions can often dramatically simplify the rule set.

Another mechanism for simplification of complex decision logic is to split an exhaustive set of rules into disjoint subtables based on common decision factors.

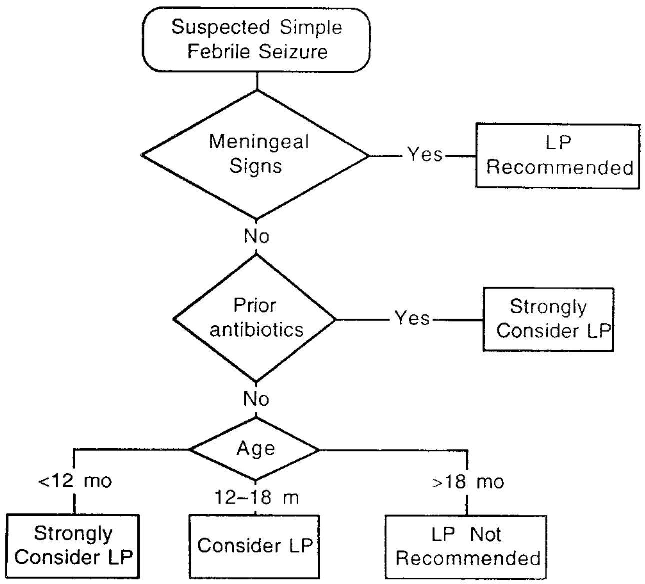

Figure 3 Conventional decision tree representation of the logic.

These logically segregated rule subsets can be "called" from a master decision table and can return values defined by the subtables' logic to the master table. This modularization was employed in a hepatitis immunization analysis to define maternal risk level based on three decision variables that are logically isolated from the rest of the immunization logic.[16]

A third mechanism for simplification of complex rule sets makes use of semantic subsumption.[48] Subsumption can be used to simplify a rule set whenever one rule's meaning is already expressed in another's that reaches the same conclusion from less restrictive conditions. Customarily, subsumption has been applied in rule-based systems by counting the number of antecedents of similar rules. Rules that reach the same conclusion with fewer antecedents may subsume those with a greater number of premises. However, subsumption may apply in cases where rules have an *identical* number of antecedents if a semantic relationship among the values allows one rule to subsume another. For example, increasing levels of cholesterol are associated with increasing risk of adverse cardiovascular events. Consider a rule set that exhaustively defines clinical circumstances for appropriate prescription of lipid-lowering medications and recognizes three levels of serum cholesterol values—low, moderate, and high. A rule specifies: IF the patient has risk factors A, B, and C, and a *moderate* level of cholesterol, THEN treat with lipid-lowering medication. One would predict that another rule in a comprehensive set would specify: IF the patient has risk factors A, B, and C, and a *high* level of cholesterol, THEN treat with lipid-lowering medication. The rule that applies to patients with moderate cholesterol semantically subsumes the rule applicable to patients with higher levels and makes it possible to collapse the recommendations into a broadened single rule. Iterative application of this process to seven cardiovascular risk factors allowed an 80% reduction in the number of rules necessary to comprehensively define the domain of recommendations for hypolipidemic medication.[48]

A decision table is usually atemporal. This may be advantageous in terms of the flexibility of the model, since decision table rule sets can provide recommendations for all combinations of decision values, regardless of the order in which they are supplied. In contrast, algorithmic representation of guidelines can leave users in limbo when the specified temporal sequence of data collection is violated.

When temporal sequencing is necessary, decision variables can be defined with temporal semantics: e.g., "Results of repeat test at 1 month post-diagnosis." Alternatively, networks of subtables can be used to represent temporally distinct decisions.

The Augmented Decision Table Model

Although conventional decision tables offer considerable capabilities for representing and manipulating guideline logic, substantial information is set aside in the process of distilling the rules. Such information includes detailed explanations of how tests and prescribed interventions are to be performed, the benefits and harms of the recommended strategies, the value

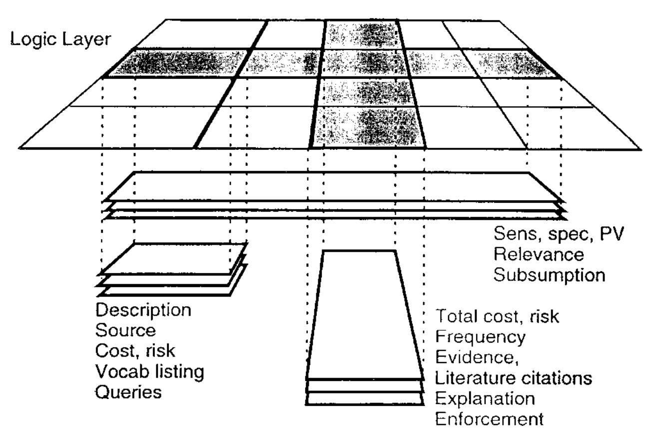

Figure 4 Augmented decision table model. Guideline logic, represented in the top layer of a multilevel table, can be augmented with many types of information, which relates to the tables' cells, rows, and columns.

and costs of the decision variables and the actions, and the quality and sources of evidence that support guideline recommendations. Such information is critical for guideline developers during guideline formulation and for the end-user of the guideline advice who is seeking greater understanding of the domain. This knowledge can also be used by an automated knowledge processor for optimization and consolidation of rule sets based on frequency and/or costs of execution.

We propose a multi-layered augmented decision table in which collateral information is stored in slots at various levels beneath the conventional decision table view of the guideline logic (Fig. 4). This augmenting information naturally relates to various components of the decision table representation—to individual cells, rows, and columns.

Augmenting Condition and Action Stubs

Cells in both the condition and action stubs make highly abbreviated statements about the decision variables and recommended actions. One layer of an augmented decision table can be dedicated to enhanced explication and description of these components. For example, a decision variable might be designated simply as "Urine culture" in the condition stub. The description layer might include the fact that the specimen should be collected by catheterization or suprapubic aspiration, and should be processed immediately by the laboratory or refrigerated at 4° Centigrade. Likewise important for decision making, each decision variable and each action has an associated cost—in money, time, and/or morbidity.

Other layers can be filled at implementation time to define the local sources of the decision variables (e.g., from patient history or from the Laboratory Information System Table HEMVALS). Controlled vocabulary listings that are used to encode the information and specific queries that manipulate it can be documented in other layers, which are linked to the stubs.

Augmenting Row Information

Each decision variable is associated with conditional probabilities—sensitivity, specificity and predictive values—which depend on the particular values of the variables. For example, a positive test is associated with true and false positive rates and a positive predictive value. These probabilities can conveniently occupy a row in a layer behind the logic.

Meta-knowledge relevant to table reduction and decomposition also can be maintained in layers that relate to decision table rows. The WDC and DELTA for each row represent information that quantifies the relevance of each decision variable to the decision at hand. Furthermore, information that identifies a subsumption hierarchy for the values of each decision variable can be linked to each row to assist in table consolidation using semantic subsumption techniques.

Augmenting Decision Table Columns

Probabilities and Utilities

The decision table can serve as a spreadsheet for summing costs and calculating joint probabilities. Each full column in the augmented table can be associated with derived values such as the sum of the costs of the testing and interventions or the joint probability of risks of the individual decision variables and actions. Regardless of the source of the data—controlled trials, decision analytic models, meta-analyses, etc.—they can be stored and manipulated in layers linked to the relevant rules.

The strategy described by each column is associated with a specific outcome and, therefore, may have an overall expected value. Moreover, the specific decision value combinations for each column can be expected to occur at some predictable frequency. These overall costs and frequencies can be used to guide table consolidation to create rule sets optimized for efficient decision making.

Tables augmented with probability and utility information were used to define a strategy for operationalizing the decision to operate or observe in suspected appendicitis.[49] Thresholds were chosen—based on predicted posterior probabilities for the diagnosis of appendicitis—for one therapeutic strategy that minimizes morbidity and another that minimizes mortality. Diagnostic decision trees were created to support both policies and to maximize the efficiency of the workup.

The model demonstrated that optimization of the augmented decision tables could produce efficient sequential strategies. Although 24 rules were required to completely specify each strategy before optimization, consolidation produced tables that completely defined each strategy in 9 and 10 rules, respectively. The efficiency of the "workups," measured by average path length, improved by 25%.

Evidence Sources and Quality

In an augmented decision table, rules can be linked to table layers, which clarify the reasoning behind a particular recommendation beyond that provided by a simple restatement of rule antecedents. That is, the rudimentary IF . . . THEN clause can be replaced by IF . . . THEN . . . ***BECAUSE***. For example, in a child with minor closed head trauma, IF there was no loss of consciousness, THEN skull radiographs are not recommended ***BECAUSE*** the substantial rate of false positive radiographs and the low prevalence of intracranial injury among this specific subset of patients lead to a low predictive value of serious injury.

Literature citations, which are instrumental in defining a specific recommendation, can also be stored in an augmented decision table layer behind the relevant recommendation. In a guideline recommendation that is determined by panel consensus, the specific levels of agreement (or disagreement) of the panel participants can be specified.[50]

The evidence and reasoning that supports a guideline recommendation is best understood by the guideline developers, but it must be transmitted to guideline implementers, who seek to design systems that influence clinical decision making, and to providers, who wish to apply clinical guidelines rationally in their practices.

An effective knowledge model must support transfer of this information among these groups.

Multiple grading systems have evolved to rate evidence quality and to define the strength of a recommendation.[51–53] Evidence quality is based on the number of studies, quality of research, number of replications, and consistency of findings in the evidence. In general, evidence provided by randomized controlled trials is considered to be of higher quality than that derived from case-control or cohort studies. These quasi-experimental studies, in turn, are superior to expert opinion.

The strength of a recommendation, however, may not correlate exactly with the quality of evidence. The strength of a recommendation is influenced by the burden of suffering of the target condition, the costs of the intervention, and other policy considerations. In the absence of high-quality scientific evidence, developers' assignments of evidence strength may depend on the level of expert consensus.

Evidence quality should help to determine the appropriate level of enforcement to apply to each recommendation when designing decision support applications.

Implementers have a range of techniques available to enforce guideline recommendations; these techniques vary from simplifying compliance by making the recommended action the default activity[8] to requiring the user to fill out detailed on-screen forms that are evaluated in real time for appropriateness.[54]

Discussion

Decision tables can serve as a unifying knowledge representation for developers and implementers of clinical practice guidelines. In contrast to the currently used methods for guideline knowledge representation during the development phase (described above), decision tables offer an opportunity for domain experts to directly express their recommendations as rule sets, thereby mitigating unintended alterations that may occur when prose and algorithmic structures are "translated" during implementation efforts.

The following desirable qualities suggest the potential effectiveness of the augmented decision table model:

- The verifiability of a decision table rule set can help to assure the logical integrity of guideline recommendations. Published guidelines are frequently deficient in terms of clarity, completeness and consistency.[8,16,56] By requiring explicit definition of decision variables and specification of allowable values, decision tables can help to identify and correct deficiencies in the logical integrity of guideline recommendations.

- Decision tables may prove to be useful during the early phases of guideline creation when the logic has not yet been defined. Developers could use "progressive rule development"—a knowledge acquisition technique that iteratively defines decision variables and actions and presents combinations to the experts in decision table format.[57] Insights into the developing knowledge base contribute to a more comprehensive understanding of the decision logic by the guideline development team; integrated verification helps to ensure a complete, unambiguous product. A controlled trial (among nonprogrammers) showed that rules could be constructed faster and more accurately with a decision table editor than a standard text editor.[55] Our group is working with the Committee on Quality Improvement of the American Academy of Pediatrics (AAP) to apply this approach in the development of forthcoming practice guidelines.

- Alternatively, guidelines can be translated into decision table rule sets for implementation after a "traditional" development process. Implementers —who are not part of a development team—can translate the prose into rules and populate the various levels of an augmented table. We have used this approach to create a pen-based system that supports compliance with a guideline for office management of asthma.[58]

- A clear display of a guideline rule set can be facilitated by decision table consolidation techniques. We have found anecdotally that the decision table display is comprehensible to domain experts, knowledge engineers, guideline implementers, and end users. Additionally, decision table decomposition techniques can be used to create sequential decision trees. Such trees can facilitate the construction of algorithmic representations of guideline knowledge.

- The modularity of the decision table representation can assist the process of guideline updating. We are currently involved in a project to provide corrective, perfective, and adaptive knowledge maintenance for several practice parameters of the AAP using augmented decision tables. Expressing these guidelines as cohesive rule sets facilitates the maintenance task.

- Decision tables are functionally equivalent to a programming language and can encode sequence, iteration, and branching.[30,57] Therefore, optimized decision tables could be executed directly by specially designed processing programs.[35] On the other hand, optimized rule sets can be incorporated into existing shells for execution.

- The clarity that is gained in the process of distilling guideline recommendations to rules is counterbalanced by a loss of supporting knowledge. Augmented decision tables can store relevant declarative knowledge and use it to guide rule set optimization. The presentation of augmented decision table "slots" to a development team can prompt the experts to provide appropriate information to fill them.

It must be noted that the augmented decision table model for guideline knowledge representation has not been validated by empiric observation of its effectiveness in guideline development or in clinical decision support. To realize the full potential of this knowledge model will require that guideline development groups become familiar with a rule-based approach to guideline knowledge representation. Currently, many informatics and information systems professionals are unfamiliar with decision table concepts. If they are to use decision tables in guideline development and implementation, they must become acquainted with this construct. Furthermore, tools must be created to permit non-experts to create, display, and manipulate augmented decision table rule sets. Finally, this approach must be evaluated to assess its effectiveness. Clearly, a limitation of any guideline model is that it simplifies clinical decision-making processes. No matter how many factors are included in the logic, guideline statements will always omit some factors that are considered by good clinicians under certain circumstances. However, we believe that any factor that can be explicitly specified—clinical, financial, social, ethical, or legal—can be included as a decision variable or an action in this knowledge representation. Factors such as cost, which may not be computable by an empirical model, can only be represented to the extent that they can be approximated.

Historically, inadequate planning for implementation is an important reason why strategic policies have failed to bring about their intended outcomes.[59,60] This is as true in the arenas of international affairs, economics, and politics as it is in health care. Guideline developers must understand and address the issues facing policy implementers to ensure that their goals are achieved. By serving as a common knowledge representation, decision tables may make a substantial contribution to guideline development and facilitate knowledge management for effective guideline implementation.

The many constructive suggestions of my colleagues and fellows at the Yale Center for Medical Informatics are appreciated.

References ■

1. Coiera EW. Artificial intelligence in medicine: the challenges ahead. J Am Med Inform Assoc. 1996;3:363–6.
2. Kulikowski CA. AIM: quo vadis? J Am Med Inform Assoc. 1996;3:432–3.
3. Bench-Capon TJM. Knowledge Representation: An Approach to Artificial Intelligence. London: Academic Press, 1990;220.
4. Wall E, Hagen M. An overview of clinical policies with implications for clinical practice, medical education, and research. Family Medicine. 1994;26:314–8.
5. Eddy DM. Comparing benefits and harm: the balance sheet. JAMA. 1990;263:2493–95.
6. Haddon DC, McCormick K, Diokno A. An annotated algorithm approach to clinical guideline development. JAMA. 1992;267:3311–4.
7. Grimshaw JM, Russell IT. Effect of clinical guidelines on medical practice: a systematic review of rigorous evaluations. Lancet. 1993;342:1317–22.
8. Tierney WM, Overhage JM, Takesue BY, et al. Computerizing guidelines to improve care and patient outcomes: the example of heart failure. J Am Med Inform Assoc. 1995;2:316–22.
9. American Medical Informatics Association. Standards for medical identifiers, codes and messages to create an efficient, computer-stored medical record. J Am Med Inform Assoc. 1994;1:1–7.
10. Pryor TA, Hripcsak G. Sharing MLM: An experiment between Columbia–Presbyterian and LDS Hospital. In: Safran

C (ed). Proc AMIA Annu Fall Symp. New York: McGraw-Hill, 1994;265–69.
11. Sherman EH, Hripcsak G, Starren J, Jenders RA, Clayton P. Using intermediate states to improve the ability of the Arden Syntax to implement care plans and reuse knowledge. In: Gardner RM (ed). Proc AMIA Annu Fall Symp. Philadelphia: Hanley & Belfus, 1995;238–42.
12. Starren J, Xie G. Comparison of three knowledge representation formalisms for encoding the NCEP cholesterol guidelines. In: Ozbolt JG (ed). Proc AMIA Annu Fall Symp. Philadelphia: Hanley & Belfus, 1994;792–6.
13. Stoufflet PE, Ohno-Machado L, Deibel SRA, Lee D, Greenes RA. GEODE-CM: a state transition framework for clinical management. In: Cimino JJ (ed). Proc AMIA Annu Fall Symp. Philadelphia: Hanley & Belfus, 1996;924.
14. Tu SW, Musen MA. The EON model of intervention protocols and guidelines. In: Cimino JJ (ed). Proc AMIA Annu Fall Symp. Philadelphia: Hanley & Belfus, 1996;587–91.
15. Shahar Y, Miksch S, Johnson P. An intention-based language for representing clinical guidelines. In: Cimino JJ (ed). Proc AMIA Annu Fall Symp. Philadelphia: Hanley & Belfus, 1996;592–96.
16. Shiffman RN, Greenes RA. Improving clinical guidelines with logic and decision table techniques: application to hepatitis immunization recommendations. Med Decision Making. 1994;14:245–54.
17. Hayward R, Wilson M, Tunis S, Bass E, Guyatt G. Users' guides to the medical literature. VIII. How to use clinical practice guidelines. A. Are the recommendations valid? JAMA. 1995;274:570–4.
18. Leape LL, Hilborne LH, Kahan JP, et al. Coronary artery bypass graft: a literature review and ratings of appropriateness and necessity. JRA-02. Santa Monica, CA. RAND, 1991.
19. Stool S, Berg A, Berman S, et al. Otitis media with effusion in young children: clinical practice guideline. Number 12. AHCPR Publication 94-0622. Rockville, MD: Agency for Health Care Policy and Research, 1994.
20. Centers for Disease Control. Hepatitis B virus: a comprehensive strategy for eliminating transmission in the United States through universal childhood vaccination: recommendations of the Immunization Practices Advisory Committee (ACIP). MMWR 1991;40(RR-13):1–25.
21. American Academy of Pediatrics Committee on Quality Improvement. Practice parameter: the neurodiagnostic evaluation of the child with a first simple febrile seizure. Pediatrics. 1996;97:769–72.
22. Adelman L. Evaluating Decision Support and Expert Systems. New York: John Wiley, 1991.
23. McCormick KA, Moore SR, Siegel RA. Clinical practice guidelines development: methodology perspectives. AHCPR Pub. No. 95-0009. Rockville, MD: Agency for Health Care Policy and Research, 1994.
24. Moret BE. Decision trees and diagrams. Comput Surv. 1982;14:593–623.
25. Reilly KD, Salah A, Yang C-C. A logic programming perspective on decision table theory and practice. Data and Knowledge Engineering. 1987;2:191–212.
26. Pooch UW. Translation of decision tables. Comput Surv. 1974;6:125–51.
27. Maes R, Van Dijk JEM. On the role of ambiguity and incompleteness in the design of decision tables and rule-based systems. Comput J. 1988;31:481–9.
28. Schneider ML. Weighted decision tables: an alternative solution for ambiguity. CACM 1985;28(4):366–371.
29. Cragun BJ. A decision-table-based processor for checking completeness and consistency in rule-based expert systems. Int J Man-Mach Stud. 1987;26:633–8.
30. Hurley RB. Decision Tables in Software Engineering. New York: Van Nostrand Reinhold, 1983;164.
31. Murphy OJ, McCraw RL. Designing storage efficient decision trees. IEEE Trans. Computers. 1991;40:315–20.
32. King PJH, Johnson RG. Conversion of decision table programs to sequential testing procedures. Comput J. 1975;18:298–306.
33. Lew A. Optimal conversion of extended-entry decision tables with general cost criteria. Comm ACM. 1978;21:269–79.
34. Colomb RM, Chung CYC. Very fast decision table execution of propositonal expert systems. In: Eighth National Conference on Artificial Intelligence. Boston, MA: AAAI Press, 1990:671–6.
35. Vanthienen J, Wets G. From decision tables to expert system shells. Data and Knowledge Engineering. 1994;13:265–82.
36. Vanthienen J, Robben F. Developing legal knowledge-based systems using decision tables. Fourth International Conference on Artificial Intelligence and Law (ICAIL). Amsterdam: The Netherlands, 1993.
37. Vanthienen J, Wets G. Building intelligent systems for management applications using decision tables. Fifth Annual Conference on Intelligent Systems in Accounting, Finance, and Management (ISAMFM). Stanford, CA, 1993.
38. Vanthienen J, Dries E. Illustration of a decision table tool for specifying and implementing knowledge based systems. Fifth International Conference on Tools with Artificial Intelligence (TAI). Boston, MA, 1993:198–205.
39. Holland RR. Decision tables: their use for the presentation of clinical algorithms. JAMA. 1975;233:455–7.
40. Karch FE, Lasagna L. Toward the operational identification of adverse drug reactions. Clin Pharmacol Ther. 1977;21:247–254.
41. Bodden WR. Adaptation of the decision table in teaching oral diagnosis. J Dent Educ. 1977;41:626–9.
42. Roberts B. A look at psychiatric decision making. Am J Psychiatry. 1978;135:1384–7.
43. Wartak J, Fenna D, Gelfand ET, Gallaghan JC. Diagnostic evaluation of chest pain using decision tables. In: Ripley KL (ed). Computers in Cardiology. Boston, MA. IEEE, 1986;235–7.
44. Schwarz V, Hohenberger P, Koehler CO, Schlag P. Setting up a decision support system with decision tables. Meth Inf Med. 1989;28:126–32.
45. Glasziou P, Hilden J. Decision tables and logic in decision analysis. Med Decis Making. 1986;6:154–60.
46. Glasziou P, Hilden J. Threshold analysis of decision tables. Med Decis Making. 1986;6:161–8.
47. Glasziou PP. Decision tables: an underutilized tool? Med Decis Making. 1994;14:207.
48. Shiffman RN, Greenes RA. Rule set reduction using augmented decision table and semantic subsumption techniques: application to cholesterol guidelines. In: Frisse M (ed). Proc AMIA Annu Fall Symp. New York: McGraw-Hill, 1992;339–43.
49. Shiffman RN, Greenes RA. Use of augmented decision tables to convert probabilistic data into clinical algorithms for the diagnosis of appendicitis. In: Clayton PD (ed). Proc AMIA Annu Fall Symp. New York: McGraw-Hill, 1991;686–90.
50. Shiffman RN, Leape LL, Greenes RA. Translation of appropriateness criteria into practice guidelines: application of decision table techniques to the RAND criteria for coronary artery bypass graft. In: Safran C (ed). Proc AMIA Annu Fall Symp. New York: McGraw-Hill, 1993;248–52.

51. U.S. Preventive Services Task Force. Guide to Clinical Preventive Services, 2nd ed. Alexandria, VA: International Medical Publishing, 1996.
52. Eddy DM. A manual for assessing health practices and designing practice policies. Philadelphia: American College of Physicians, 1992.
53. Jacox A, Carr D, Payne R, et al. Management of Cancer Pain. Clinical Practice Guideline. AHCPR 94-0592. Rockville, MD: Agency for Health Care Policy and Research, 1994.
54. Lepage E, Gardner R, Laub R, Jacobson J. Assessing the effectiveness of a computerized blood order ''consultation'' system. Proc AMIA Annu Fall Symp. New York: McGraw-Hill, 1991;33–7.
55. Santos-Gomez L, Darnell M. Empirical evaluation of decision tables for constructing and comprehending expert system rules. Knowledge Acquisition. 1992;4:427–44.
56. Shiffman RN. Clinical guidelines in medical practice. J Med Practice Management. 1993;9:70–4.
57. CODASYL. A Modern Appraisal of Decision Tables. New York: Association for Computing Machinery, 1982.
58. Shiffman RN. Toward effective implementation of a pediatric asthma guideline: integration of decision support and clinical workflow support. In: Ozbolt J (ed). Proc AMIA Annu Fall Symp. Philadelphia: Hanley & Belfus, 1994;797–801.
59. Goodes M. Seizing the competitive initiative: strategic planning in the health care field. In: Simyar F, Lloyd-Jones J (ed). Strategic management in the health care sector. Englewood Cliffs, NJ: Prentice-Hall, 1988;136–42.
60. Pressman J. Implementation: How Great Expectations in Washington Are Dashed in Oakland: Or, Why It's Amazing that Federal Programs Work At All, 3rd ed. Berkeley, CA: University of California Press, 1984.