Published in final edited form as:

J Eval Clin Pract. 2009 December ; 15(6): 1171–1176. doi:10.1111/j.1365-2753.2009.01310.x.

IS THERE A DOWNSIDE TO CUSTOMIZING CARE? IMPLICATIONS OF GENERAL AND PATIENT-SPECIFIC TREATMENT STRATEGIES

Peter J. Veazie, PhD[Assistant Professor],

Department of Community and Preventive Medicine, University of Rochester Medical Center, 601 Elmwood Ave. — Box 644, Rochester, NY 14642. peter_veazie@urmc.rochester.edu

Paul E. Johnson, PhD[Professor], and

Department of Information and Decision Sciences, University of Minnesota, 4-237 CarlSMgmt, 321 19th Ave S, Minneapolis, MN 55455

Patrick J. O'Connor, MD, MPH[Senior Investigator]

HealthPartners Research Foundation, PO Box 1524 Mail Stop: 21111R, Minneapolis, MN 55440-1524

Abstract

The use of general clinical guidelines versus customization of patient care presents a dilemma for clinicians managing chronic illness. We propose that the performance of customized strategies for the management of chronic illness depends on accurate patient categorization, and inaccurate categorization can lead to worse performance than that achievable using a general clinical guideline. This paper is based on an analysis of a basic utility model differentiating outcomes between the use of general management strategies and customized strategies. Results of the analysis have four implications regarding the design and use of clinical guidelines and customization of care: (1) the balance between the applications of more general strategies versus customization depends on the specificity and accuracy of the strategies; (2) adoption of clinical guidelines may be stifled as the complexity of guidelines increases to account for growing evidence; (3) clinical inertia (i.e. the failure to intensify an indicated treatment) can be a rational response to strategy specificity and the probability of misapplication; and, (4) current clinical guidelines and other decision-support tools may be improved if they accommodate the need for customization of strategies for some patients while providing support for proper categorization of patients.

Keywords

Treatment strategies; chronic disease; clinical guidelines; clinical inertia; patient safety; diabetes mellitus

INTRODUCTION

The choice between the use of general clinical guidelines versus customization of care presents a dilemma for the practicing clinician: whereas the use of guidelines is intended to decrease practice variation, customization typically increases practice variation. Guidelines

Correspondence to: Peter J. Veazie.

CONFLICTS OF INTEREST. The authors have no conflicts of interest to declare.

provide evidence-based recommendations to assist healthcare providers in organizing and applying current healthcare knowledge to clinical situations; however, currently available guidelines cannot account for the particularities of individual patients. Customization, on the other hand, is based on the application of specific strategies to the individual needs of patients; unfortunately, this can lead to undesirable variation in clinical practice when providers place too much emphasis on personal experiences relative to science-based evidence (hence, the motivation for evidence-based guidelines). The move from the dilemma of clinical guidelines versus customization of care to the integration of clinical guidelines with customization of care has appropriately been advocated as a sensible approach (1). However, we propose there remains a downside to the customization of care: namely, the potential for decreased adoption of guidelines and increased clinical inertia (failure to intensify an indicated treatment (2-3)).

Much of medical care is designed to cure illness and mend injuries; the duration of such care is typically short-term and success is defined by restoration of normal physiology or functionality. Chronic illness is an exception to this model because, although often preventable, the underlying pathophysiology is seldom curable. Instead, the treatment of chronic illness focuses on controlling pathophysiologic states in order to minimize adverse consequences over the lifetime of the patient. Consequently, the care of chronic disease is long-term and success is defined by control of pathophysiologic processes.

For many chronic illnesses, the patient's state of health eventually deteriorates, and depending on the illness can lead to death. The natural history of these diseases may often be tractable to treatment that slows the progression of the underlying pathophysiology, and may delay or prevent complications that impair function, reduce quality of life, and shorten life expectancy. The challenge faced by physicians is to develop treatment strategies that control the disease process and delay or prevent adverse consequences. Successful treatment strategies aim to maintain health-states in acceptable ranges for the longest possible length of time.

From the perspective of the healthcare provider, treatment strategies can be tailored to categories, or types, of patients—the essence of customization of care. Categorization reduces the complexity of the information and knowledge to be processed and reduces effort associated with making choices among decision alternatives (4-7). Useful categories embed information that accrues advantages to customized treatment strategies over more general strategies (i.e. strategies that are not tailored to specific patient categories). Experience leads to improved performance through refinement of categories and better decision heuristics (5-8-9).

To be effective, patient categories must account for influences on a patient's future health state; consequently, factors that govern physician and patient behavior can be important contributors to patient categorization. Researchers have proposed that physicians use psychosocial dimensions (e.g. adherence behavior) as well as disease states to develop a patient category structure having finer granularity than medical diagnosis alone (10-11). Treatment strategies based on these additional dimensions reflect relevant variation across categories and may outperform more general strategies, including those developed as clinical practice guidelines.

In what follows we compare two kinds of strategies: those that are applied without regard to patient categories and those that are tailored to specific categories. We label the former general strategies and the latter customized strategies. The definitions of general versus customized is based on rules for strategy application. The more general a strategy is, the greater the scope of patient types that falls within its intended application. Note the general

versus custom partition of strategies is useful for the purposes of our discussion here; however, strategies vary along a general to specific continuum.

We characterize treatment strategies by performance and specificity. Performance provides a normative measure of how well a strategy controls patient health trajectories; specificity reflects the difference in performance between a given category and the remaining categories (as a whole). Figure 1 illustrates a measure of specificity based on the differences denoted as S_1 and S_2 . Dividing S_1 and S_2 by each respective strategy's highest performance gives a measure of relative specificity. Notice that strategy 1 has specificity of 0, implying no difference in performance between patient categories; whereas strategy 2 has a positive specificity for category A. Specificity is category dependent: a strategy may be highly specific with respect to one category but less specific with respect to another category. For example, consider, for convenience of calculation, three equal size categories of people labeled category A, B, and C, and a strategy that has an average performance in each category of 1, 2, and 3 respectively. The relative specificity of the strategy with respect to category C is $0.3 = (3-1.5)/3$, that is the relative difference between performance within the target category and performance outside the target category. The relative specificity with respect to category B, however, is $0 = (2-2)/2$.

Although both general and specialized strategies vary in performance and specificity, when discussing a specialized strategy we typically consider the specificity with respect to the category for which the strategy was created. We propose that categorization generates a relationship between performance and specificity whereby better performance is achieved through greater specificity. When applied to patients for whom they are intended, specialized strategies are expected to outperform general strategies, and strategies with higher specificity are expected to outperform those with lower specificity.

Higher specificity implies greater variation in performance across patient categories. Consequently, applying a treatment strategy tailored for one category to patients belonging to another category can markedly decrease treatment effectiveness. The misapplication of a strategy may result from misclassification or mechanization error (12, 13). Misclassification occurs when an object is mistakenly deemed a member of a class, and mechanization errors occur when an object is mistakenly deemed sufficiently similar to a class to warrant application of the corresponding strategy. Errors are likely when switching attention between tasks is hindered and cognitive resources are diminished (14, 15): situations that can characterize the practice environment (16). However, the availability of genetic markers for risk and treatment response may provide increased accuracy of patient classification in the future (17). In summary, we propose that strategies can be misapplied and those with high specificity may not be desirable if they are applied to patients in other categories. The following analysis of this proposition has four specific implications that we present in the discussion section.

ANALYSIS

In this section we use a simple expected utility model to provide an analysis of necessary conditions for preferring more general treatment strategies to customized or more specialized strategies. We represent patient categories as a partition Σ on a patient state space $\mathbf{S}$. Each element of a partition comprises the patient states that compose a patient category. Patient categories are related to treatment strategies by a function g that maps $\{\mathbf{S}\} \cup \Sigma$ onto a subset $\mathbf{A}$ of all possible treatment strategies. The elements σ of the partition Σ are indexed by $i \in \{1, \dots, k\}$ where k is the total number of patient categories. Treatment strategies $a \in \mathbf{A}$ are indexed by $j \in \{0, 1, \dots, k\}$. The index $j = 0$ denotes a general treatment strategy (i.e. a strategy that applies to the full set of patients, $a_0 = g(\{\mathbf{S}\})$); the remaining

indices match the corresponding elements of the partition and indicate specialized strategies (i.e. $a_j = g(\sigma_i)$ for all $j = i$). We denote strategy performance by u_{ij} : the utility associated with applying treatment strategy $a_j \in \mathbf{A}$ to a patient in category $\sigma_i \in \Sigma$. The following matrix represents the performance (utility) structure relative to σ_i and a_j :

$$\begin{array}{c|ccccc}
 & \text{Physician Strategies} \\
 & a_0 & a_1 & a_2 & \cdots & a_k \\
 \text{Patient Categories} & \sigma_1 & u_{10} & u_{11} & u_{12} & \cdots & u_{1k} \\
 & \sigma_2 & u_{20} & u_{21} & u_{22} & \cdots & u_{2k} \\
 & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
 & \sigma_k & u_{k0} & u_{k1} & u_{k2} & \cdots & u_{kk} \\
 & \underbrace{\phantom{u_{i0}}} & \underbrace{\phantom{u_{i1}}} & \underbrace{\phantom{u_{i2}}} & \underbrace{\phantom{u_{i3}}} & \underbrace{\phantom{u_{i4}}} & \underbrace{\phantom{u_{ik}}} \\
 & \mathbf{U}^0 & & & & & \mathbf{U}^*
 \end{array}$$

(1)

The matrix labeled $\mathbf{U}^*$, containing elements $\{u_{ij}: i, j \geq 1\}$, comprises the utilities for specialized strategies (a_1 through a_k). The diagonal of $\mathbf{U}^*$ contains utilities associated with the patient categories for which the specialized strategies are tailored (i.e. patient categories $g^{-1}(a_j)$ for all $j \geq 1$). Each column of $\mathbf{U}^*$ comprises the utilities of a particular strategy a_j for all patient states σ_i . The column vector labeled $\mathbf{U}^0$, containing elements $\{u_{i0}: i \geq 1\}$, comprises the utilities of the general strategy across patient categories.

We analyze three models, each constrained by two assumptions: First, we assume for each treatment strategy a_j the utility associated with the patient category $\sigma_i = g^{-1}(a_j)$ is greater than or equal to the utility of that strategy applied to other categories (i.e. $u_{mm} \geq u_{im}$ across i for each $m \geq 1$). This embodies the proposition that treatment strategies are tailored to specific patient categories by virtue of better performance. Second, we assume the distribution of patients across categories is independent of the treatment strategy decision (although the distribution may be a function of past decisions). This reflects an ontological commitment to the proposition that causes precede effects.

Expected utility theory implies the general treatment strategy a_0 is preferred to the set of specialized strategies $\{a_1, \dots, a_k\}$ if the expected utility associated with the use of a_0 exceeds the expected utility of using the set $\{a_1, \dots, a_k\}$, i.e.

$$E(u_{ij}|a_0) > E(u_{ij}|\{a_1, \dots, a_k\}). \quad (2)$$

The expected utility of the general strategy (the left side of equation 2), relative to a probability mass function p , is

$$E(u_{ij}|a_0) = \sum_i (u_{i0} \cdot p(\sigma_i)). \quad (3)$$

The first model we consider is based on two additional assumptions: first, for each patient category σ_i the utility of the general strategy is proportional by a constant factor β to the optimal utility associated with the specialized strategy $a_j = g(\sigma_i)$; and second, the probability of correctly categorizing a patient is the same across categories. The first assumption implies

$$u_{i0} = \beta \cdot u_{ii} \quad (4)$$

for all i , where β is the proportionality factor representing the relative utility of the general strategy relative to the ideal implementation of the specialized strategy. From equation 3, the general strategy's expected utility is rewritten as

$$E(u_{ij}|a_0) = \beta \cdot \sum_i (u_{ii} \cdot p(\sigma_i)). \quad (5)$$

Denoting the expected utility for $i = j$ as $\bar{u}_{i=j}$ (with respect to the marginal distribution $p(\sigma)$), equation 5 becomes

$$E(u_{ij}|a_0) = \beta \cdot \bar{u}_{i=j}. \quad (6)$$

The expected utility of specialized strategies (the right side of equation 2) is

$$E(u_{ij}|\{a_1, \dots, a_k\}) = \sum_{i,j,m} u_{ij} \cdot p(a_j|\sigma_i, m) \cdot p(m|\sigma_i) \cdot p(\sigma_i). \quad (7)$$

In this formulation m is a dichotomous variable for which $m = 0$ represents correct categorization of a patient, and $m = 1$ represents incorrect categorization of a patient. Denoting the probability of correct categorization as π (i.e. $\pi = p(m = 0 | \sigma_i)$ for all i categories), equation 7 can be written as

$$E(u_{ij}|\{a_1, \dots, a_k\}) = \pi \cdot \sum_i (u_{ii} \cdot p(\sigma_i)) + (1 - \pi) \cdot \sum_i (p(\sigma_i) \cdot \sum_{j \neq i} (u_{ij} \cdot p(a_j|\sigma_i, m=1))) \quad (8)$$

or simply

$$E(u_{ij}|\{a_1, \dots, a_k\}) = \pi \cdot \bar{u}_{i=j} + (1 - \pi) \cdot \bar{u}_{i \neq j}, \quad \forall (i, j) \geq 1, \quad (9)$$

where $\bar{u}_{i \neq j}$ denotes the expected value of utility for misapplication of the strategies. Substituting equations 6 and 9 into equation 2 and solving for β gives the necessary condition for preferring the general strategy to the specialized strategies in this model:

$$\beta > \pi + (1 - \pi) \cdot \frac{\bar{u}_{i \neq j}}{\bar{u}_{i=j}}. \quad (10)$$

As discussed in the introduction, relative specificity is defined as the ratio $\frac{\bar{u}_{i=j} - \bar{u}_{i \neq j}}{\bar{u}_{i=j}}$, which

is $1 - \frac{\bar{u}_{i \neq j}}{\bar{u}_{i=j}}$. Defining the ratio $\frac{\bar{u}_{i \neq j}}{\bar{u}_{i=j}}$ as the relative generality γ (i.e., one minus the relative specificity) of the strategies $\{a_1, \dots, a_k\}$, equation 10 can be written as

$$\beta > \pi + (1 - \pi) \cdot \gamma.$$

Because we assume $\bar{u}_{i \neq j} \leq \bar{u}_{i=j}$, relative generality γ is less than or equal to 1. As the relative generality γ approaches 1, the specialized strategies perform equally well across patient

categories; consequently, there is no cost associated with incorrect categorization and the relative utility β of the general strategy must exceed 1 to prefer the general strategy. Similarly, as the probability of correct classification π approaches 1, the chance of incurring a cost due to incorrect categorization diminishes toward 0, and again, β must exceed 1 to prefer the general strategy. In either case, the general strategy must perform better than the correct application of the specialized strategies for β to exceed 1. As γ approaches 0 the specialized strategies do not function for patient categories where $i \neq j$, this implies a greater cost associated with incorrect categorization. In this case, the second term on the right side of equation 10 is 0, implying the relative performance of the general strategy must exceed the probability of misclassification.

Figure 2 shows a contour plot of β on the parameter space defined by π and γ . The maximum of π and γ defines the lower bound of β for preferring the general strategy; the lower bound is achieved if the minimum of π and γ is equal to 0. For example, a physician using specialized strategies with γ near 0 and a 0.8 probability of correctly categorizing patients must have a general strategy that performs better than 80% of the specialized strategies' performance if the general strategy is to be preferred. As γ increases, the lower bound of the general strategy's performance is higher. This result conforms to intuition: as generality increases, the cost of incorrect categorization is diminished and a competing general strategy must increase performance to remain the preferred strategy. Similarly, for a given level of generality, as the probability of correctly categorizing patients increases, the probability of incurring a loss due to incorrect categorization decreases; again, a general strategy would require better performance to compete with the increased accuracy with which the specialized strategies are applied.

The preceding model assumes β is constant across patient categories. A model in which β varies across categories can be analyzed by expressing the utilities of the general strategy as a proportion of the mean utility across u_{ij} for $i = j$ of the specialized strategies. Substituting

$$u_{i0} = \beta_i \cdot \bar{u}_{i=j} \quad (11)$$

into equation 3 gives

$$E(u_{ij}|a_0) = \bar{u}_{i=j} \cdot \sum_i (\beta_i \cdot p(\sigma_i)). \quad (12)$$

Following a derivation similar to that used in the preceding analysis, the necessary condition for preferring the general strategy in this case is similar to that represented by equation 10 above, specifically

$$\bar{\beta} > \pi + (1 - \pi) \cdot \frac{\bar{u}_{i \neq j}}{\bar{u}_{i=j}}. \quad (13)$$

Here $\bar{\beta}$ denotes the mean relative performance of the general strategy representing the summation in equation 12. Figure 2 and the conclusions of the preceding analysis apply to this model as well, but we consider the mean relative performance $\bar{\beta}$ in place of β .

Both analyses presented above assume the probability of correct categorization is independent of patient categories. Without this assumption, we can only state a general criterion for the preference of the general strategy. From equations 2 and 12 the necessary condition is

$$\bar{\beta} > \frac{E(u_{ij}|\{a_1, \dots, a_k\})}{\bar{u}_{i=j}}. \quad (14)$$

The numerator in the right side term of the inequality is equal to or less than the denominator with equality only when the probability of correct classification is 1. A general strategy must therefore perform better on average across patient categories than specialized strategies relative to the optimal performance of the specialized strategies (i.e. relative to the expected utility of correctly applied specialized strategies). Factoring equation 14 and rewriting gives

$$\bar{\beta} > \sum_i p(\sigma_i) \cdot \left(\underbrace{\frac{(\pi_i \cdot u_{ii})}{\bar{u}_{i=j}}}_A + \frac{\left((1 - \pi_i) \cdot \sum_{j \neq i} (u_{ij} \cdot p(a_j|\sigma_i, m=1)) \right)}{\underbrace{\bar{u}_{i=j}}_B} \right). \quad (15)$$

This formulation reveals two category-specific components: (1) the decrease in performance due to the probability of not applying specialized strategies to the targeted category (represented by the first term in the parentheses on the right side of the inequality, indicated as part A); and, (2) the modifying affect of a non-zero utility associated with misapplying treatment strategies (represented by the second term on the right side of the inequality, indicated as part B). The import of these components is based on the probability of correct categorization π_i , and the utilities u_{ij} . If patients are always correctly categorized (i.e. $\pi_i = 1$ for all i), or if each specialized strategy performs equally well across categories (i.e. $u_{ii} = u_{ij}$ for all $j \geq 1$), then the first term equals 1 and the second term equals 0. In this case, the general strategy must outperform the optimal application of the specialized strategies, which would contradict the assumption that specialization is driven by improved utility. If patients are always incorrectly categorized ($\pi_i = 0$ for all i), then the first term is equal to 0 and the general strategy must outperform the consistent misapplication of the specialized strategies. If the utilities u_{ij} equal 0 for all $i \neq j$ (i.e. the off-diagonal elements of $\mathbf{U}^*$), the second term is 0 and $\bar{\beta}$ is bound solely by the relative performance of the diagonal elements of $\mathbf{U}^*$.

In this section we identified necessary conditions for preferring general strategies based on the model presented in matrix 1. We compared the use of general strategies versus a number of specialized strategies considered as a set. Alternatively, general strategies can be compared with each specialized strategy individually. Results would be the same as those presented here, only they would apply separately to each column of $\mathbf{U}^*$.

DISCUSSION

We have shown that customized (category-specific) treatment strategies based on performance under optimal conditions may not be preferred due to the effects of specificity and faulty patient categorization. However, when such treatment strategies are appropriately applied, the expected outcome using more specific strategies should exceed the expected outcome using less specific strategies. This result implies customizing treatment strategies to patient categories will be successful only if patient categorization is reasonably accurate. As the probability of applying a category-specific strategy to patients of another category increases, the advantage of customization is diminished. The fact that approximately 25% of adults have multiple chronic diseases increases the potential benefits of customized

treatment strategies, though only if the strategies are evidence-based with respect to the interactions of the multiple chronic diseases (18-19). Consider, for example, the use of depression drugs such as the tricyclics also have beneficial effects on neuropathy pain; an advantage can accrue to strategies that utilize the dual benefits of such drugs if patients are properly identified. However, correct classification can be imperative; for example, if a diabetes patient has undetected heart failure, and is treated with thiazolidinediones for better glucose control, a life-threatening episode of uncompensated heart failure may result. Moreover, customized strategies seem more desirable for older and sicker patients with diabetes because the long-term benefits of glucose control diminish, while the short-term risks of aggressive treatment strategies to control glucose increase (20).

When the probability of appropriate patient categorization is less than 1, the use of treatment strategies with lower specificity may be preferred. In such circumstances it is not necessary that the strategy with lower specificity have a high level of performance; the only requirement is that the lower specificity strategy performs *better* than the *misapplication* of the strategy with high specificity, which can lead to an overall low level of performance. If treatment strategies are too specific and there is a possibility of incorrect categorization, policies that customize strategies to manage chronic illness may fail. The benefits of customizing strategies to patient categories as an alternative to the more general strategies such as those found in some clinical guidelines should be considered in light of specificity and the expected accuracy of the categorization process.

Based on the preceding analysis we arrive at four implications regarding a tradeoff between general and customization of care. *First, the balance between the applications of more general strategies versus customization depends on the specificity and accuracy of the strategies.* The implication is that balancing clinical guidelines with customization, which is rightfully encouraged (1), should account for the probability and consequence of misapplication. In the face of variation in classification skills and treatment strategy effectiveness, the proper balance is idiographic and belies a single rule applicable across providers. Providers with highly specific strategies and excellent skill at patient classification may benefit from more customization; providers with highly specific strategies and poor skill at patient classification may do well to remain anchored closer to the guidelines; and, providers with only slightly specific strategies may have greater flexibility in striking an appropriate balance. The introduction of genetic markers of risk and treatment responses may improve the ability of nearly all physicians to classify patients in the future.

Second, adoption of clinical guidelines may be stifled as the complexity of guidelines increases to account for growing evidence. As guidelines transition from general to more specific they may increase in both the probability of misapplication and potential cost of misapplication. This implies greater hesitancy of guideline adoption among those who account for the specificity and the probability of misapplication in making clinical judgments. As genetic predictors of disease risk become available, the use of general treatment strategies may fade and be gradually replaced by customized treatment (or prevention) strategies guided by genetic predictors of complication risks and treatment response (17). For example, the use or non-use of certain blood pressure medications may be guided by an individual patient's genetic markers of renin-angiotensin-aldosterone pathway function; effective use of such a treatment strategy will depend on proper patient classification. In summary, we expect guidelines that are too general may garner little endorsement due to a lack of patient-specific applicability, whereas guidelines of greater complexity, and consequent increase in specificity, may experience low application because of provider hesitancy to potentially incur the consequences of misapplication.

Third, clinical inertia (i.e. the failure to intensify an indicated treatment (2-3)) can be a rational response to strategy specificity and the probability of misapplication. Recognizing the implications of specificity and accuracy regarding specialized strategies, physicians may rationally engage clinical inertia to avoid the consequences of misapplying intensification strategies, particularly when such strategies involve using multiple medications in which there can be a considerable cost of misapplication (21). The classic clinical example of this problem is the elderly patients with multiple chronic conditions. In such a patient, long-term benefits of better chronic disease control are mitigated by circumscribed life expectancy, and the side effects and risks of polypharmacy are increased (22-24). Moreover, the application of specific strategies for one chronic disease may make another chronic disease worse. For example, treating lung dysfunction with steroids worsens glucose control which is needed because of diabetes, or in another case treating diabetes with certain classes of drugs may increase the risk of congestive heart failure. More generally, we could expect to find a greater tendency for clinical inertia among physicians who are less confident in using complex treatment strategies and who have a high proportion of their patients present as more complicated cases, thereby making accurate categorization less certain.

Finally, current clinical guidelines and other decision-support tools may be improved if they accommodate the need for customization of strategies for some patients (perhaps by limiting the pool of patients for whom they are intended to guide care), while providing support for proper categorization of patients. This may provide an important change to tools directed at facilitating clinical goals. For instance, when many standard treatments are of potential benefit to a patient, a customization algorithm could be applied to inform the physician and patient which of the many potential treatments provide maximal benefit, or maximal cost-effectiveness, based on characteristics of the individual patient, such as age, specific comorbidities, kidney function, body mass index, or other factors.

The findings presented in this paper are quite general. The proposition that specificity of a strategy and accuracy of categorization combine to influence the consequence of implementing strategies of varying utility is applicable to the development and application of any treatment strategy for which variation in performance is possible. And, the definition of performance in this case can include any measure of interest—for example, among others, the health benefit, cost-effectiveness, and profitability of strategies all fit into the present scheme and can be important considerations in evaluating treatment strategies in the manner presented here.

Acknowledgments

We wish to thank William Rush, PHD, of HealthPartners Research Foundation, Minneapolis Minnesota, for his helpful review and comments regarding previous drafts of this manuscript.

SOURCES OF SUPPORT. This project was supported in part by AHRQ grants HS11919 and HS10639, and NIH grant DK068314.

REFERENCES

1. O'Connor PJ. Adding value to evidence-based clinical guidelines. JAMA. 2005; 294(6):741-743. [PubMed: 16091578]
2. Phillips LS, Branch WT Jr, Cook CB, Doyle JP, El-Kebbi IM, Gallina DL, et al. Clinical Inertia. Annals of Internal Medicine. 2001; 135(9):825-834. [PubMed: 11694107]
3. Ziemer DC, Miller CD, Rhee MK, Doyle JP, Watkins C Jr, Cook CB, et al. Clinical Inertia Contributes to Poor Diabetes Control in a Primary Care Setting. The Diabetes Educator. 2005 July 1; 31(4):564-571. 2005. [PubMed: 16100332]

4. Markman AB, Ross BH. Category use and category learning. *Psychological Bulletin*. 2003; 129(4): 592–613. [PubMed: 12848222]
5. Gigerenzer, G.; Todd, PM.; Gigerenzer, G., editor. *Simple Heuristics That Make Us Smart*. Stich, S., editor. New York: Oxford University Press; 1999.
6. Payne JW, Bettman JR. Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory and Cognition*. 1988; 14(3):534–552.
7. Payne, JW.; Bettman, JR.; Johnson, EA. *The Adaptive Decision Maker*. New York: Cambridge University Press; 1993.
8. Yamauchi T, Markman AB. Inference using categories. *Journal of Experimental Psychology: Learning, Memory and Cognition*. 2000; 26(3):776–795.
9. Murphy GL, Ross BH. Predictions from uncertain categorizations. *Cognitive Psychology*. 1994; 27:148–193. [PubMed: 7956106]
10. Johnson PE, Veazie PJ, O'Connor PJ, Pottoff SJ, Kochever L, Verma D, et al. Understanding Variation in Chronic Disease Outcomes. *Health Care Management Science*. 2002; 5(3):175–189. [PubMed: 12363045]
11. O'Connor PJ, Crabtree BF, Yanoshik MK. Differences between diabetic patients who do and do not respond to a diabetes care intervention: a qualitative analysis. *Family Medicine*. 1997; 29(6): 424–428. [PubMed: 9193915]
12. Cherubini P, Mazzocco A. From models to rules: Mechanization of reasoning as a way to cope with cognitive overloading in combinatorial problems. *Acta Psychologica*. 2004; 116:223–243. [PubMed: 15222968]
13. Woltz DJ, Gardner MK, Bell BG. Negative transfer errors in sequential cognitive skills: strong-but-wrong sequence application. *Journal of Experimental Psychology: Learning, Memory and Cognition*. 2000; 26(3):601–625.
14. Bell BG, Gardner MK, Woltz DJ. Individual differences in undetected errors in skilled cognitive performance. *Learning and Individual Differences*. 1997; 9(1):43–61.
15. Woltz DJ, Gardner MK, Gyll SP. The role of attention processes in near transfer of cognitive skills. *Learning and Individual Differences*. 2000; 12:209–251.
16. Groopman J, Hartzband P. Why 'Quality' Care is Dangerous. *Wall Street Journal*. 2009 April 8.
17. Doria A, Wojcik J, Xu R, Gervino EV, Hauser TH, Johnstone MT, et al. Interaction Between Poor Glycemic Control and 9p21 Locus on Risk of Coronary Artery Disease in Type 2 Diabetes. *JAMA*. 2008 November 26; 300(20):2389–2397. 2008. [PubMed: 19033589]
18. Boyd CM, Darer JD, Boulton C, Fried LP, Boulton L, Wu AW. Clinical Practice Guidelines for Older Patients With Comorbid Diseases--Reply. *JAMA*. 2006 January 4. 295(1):34-a-5. 2006. [PubMed: 16391210]
19. Tinetti ME, Bogardus ST Jr, Agostini JV. Potential Pitfalls of Disease-Specific Guidelines for Patients with Multiple Conditions. *N Engl J Med*. 2004 December 30; 351(27):2870–2874. 2004. [PubMed: 15625341]
20. The Action to Control Cardiovascular Risk in Diabetes Study G. Effects of Intensive Glucose Lowering in Type 2 Diabetes. *N Engl J Med*. 2008 June 12; 358(24):2545–2559. 2008. [PubMed: 18539917]
21. Gigerenzer, G.; Todd, PM.; Olsson, H. Understanding cognitive biases as a reflection of the environment. In: Todd, PM.; Gigerenzer, G., editors. *Ecological Rationality: Intelligence in the World*. New York: Oxford University Press; In Press
22. Boyd CM, Darer J, Boulton C, Fried LP, Boulton L, Wu AW. Clinical Practice Guidelines and Quality of Care for Older Patients With Multiple Comorbid Diseases: Implications for Pay for Performance. *JAMA*. 2005; 294:716–724. [PubMed: 16091574]
23. Boyd CM, Darer JD, Boulton C, Fried LP, Boulton L, Wu AW. Clinical Practice Guidelines for Older Patients With Comorbid Diseases--Reply. *JAMA*. 2006; 295:34–35. [PubMed: 16391210]
24. Tinetti ME, Bogardus ST Jr, Agostini JV. Potential Pitfalls of Disease-Specific Guidelines for Patients with Multiple Conditions. *New England Journal of Medicine*. 2004; 351:2870–2874. [PubMed: 15625341]

Figure 1. Strategy specificity. The specificity of a given strategy across two categories is denoted by S_{Category} . Strategy 2 is more specific than strategy 1; strategy 1 is nonspecific ($S_2=0$), and strategy 1 performs worse than strategy 2 in category A but better in category B.

Figure 2. Contour map of a general strategy's relative performance β on the space defined by relative generality γ and the probability of correct patient categorization π . The contour lines represent levels of β ; the arrow from the origin indicated the direction of increasing β .