Information Gathering and Integration as Sources of Error in Diagnostic Decision Making

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This research examined the relative importance of information gathering versus information utilization in accounting for errors in diagnostic decision making. Two experiments compared physicians' performances under two conditions: one in which they gathered a limited amount of diagnostic information and then integrated it before making a decision, and the other in which they were given all the diagnostic information and needed only to integrate it. The physicians: 1) frequently failed to select normatively optimal information in both experimental conditions; 2) were more confident about the correctness of their information selection when their task was limited to information integration than when it also included information gathering; and 3) made diagnoses in substantial agreement with those indicated by applying normative procedures to the same data. Physicians appear to have difficulties recognizing the diagnosticity of information, which often results in decisions that are *pseudodiagnostic* or based on diagnostically worthless information. *Key words:* diagnostic reasoning; information gathering; information integration; Bayes' theorem; medical decision making. **(Med Decis Making 1991;11:233–239)**

Diagnostic hypotheses play a prominent role in many of the tasks subsumed under the rubric of medical problem solving. Frequently, physicians consider several diagnostic hypotheses as possible explanations for a patient's problem, searching for evidence that will identify one hypothesis as "correct" or as a usable working diagnosis. A prominent characteristic of these hypotheses is uncertainty. In most diagnostic problems, physicians must deal with some degree of uncertainty about the validity and accuracy of the hypotheses they are considering. The uncertainty attending a hypothesis rises and falls as the physician obtains evidence that supports one hypothesis at the expense of others. The physicians' goal in the diagnostic problem can be viewed as arriving at some acceptable level of confidence or certainty about the validity of one of the hypothesis set.[1,2]

Generally, physicians achieve this level of confidence by gathering clinical data to test or evaluate the hypotheses under consideration. This information gathering process distinguishes medical problem solving from problems used in research in many other domains, such as physics, mathematics, and chess. In these areas, problem solvers usually have all the necessary and relevant information, so the task is to integrate this information in appropriate ways to determine the solution. In medicine, physicians rarely start with all the necessary and relevant information. Instead, they must actively seek out information in as timely and efficient a manner as possible, given the concomitant costs attached to such information gathering.

Numerous studies have examined how physicians and laymen gather information in such tasks and have identified a number of problems. Among the identified biases and limitations are: 1) tendencies toward overconfidence about the quality of one's knowledge and decisions,[3–5] 2) conservatism in probability adjustments,[6,7] 3) ignoring base-rate or prevalence information,[8–11] 4) misestimations of probabilities,[6,12–15] 5) selecting information that confirms rather than disconfirms expectations,[3,16,17] and 6) misjudging the value or meaning of information.[16,18–20]

While these biases do not necessarily lead to decision errors, it is still important to understand better the nature of their prevalence and operation. One issue in this understanding is to determine *where* in the decision making process biases occur. The process of decision making can be broken down into several components: 1) the generation of possible hypotheses, 2) the gathering of information, 3) the organization or integration of that information, and 4) the evaluation of the various alternatives in light of this information. These components generally operate in a sequential and cyclic manner such that the outcome of each stage becomes the input of the subsequent stage. For example, the hypotheses generated typically guide the

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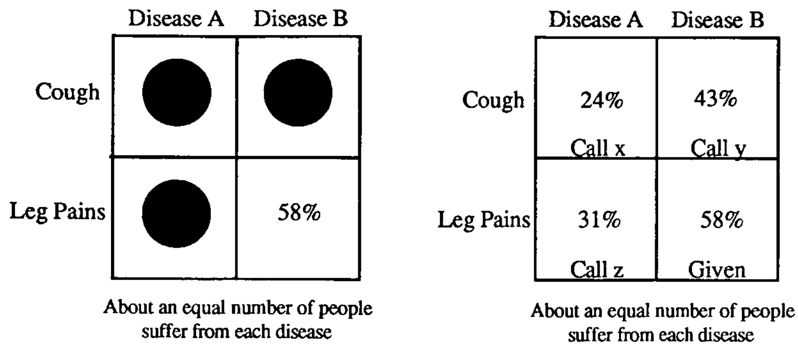

FIGURE 1. The two versions of the research problem in experiment 1. The left matrix illustrates the partial-information problem in which physicians were asked to select only one of the covered cell values by removing an opaque sticker. The right matrix illustrates the full-information version in which physicians were asked to indicate which one "call" they would choose as most important.

gathering and interpretation of information,[21] the information gathered constitutes what is available for integration and use, how the information is integrated or organized influences how it is evaluated, and the results of the evaluation may change the hypotheses, which in turn guide the gathering of information in the next cycle of the process.

Because each stage is dependent on the operation of the preceding stage, the decision-making chain can be only as strong as its weakest link. It is important to distinguish among the possible sources of errors when attempting to improve decision making. If decision errors are more attributable to deficiencies in one of these components (such as information gathering) than another (such as information integration),[22] it would suggest quite different means for improving decision making through education and decision-support techniques.

In the two experiments described in this paper, we attempted to distinguish between the information gathering and the information integration components as possible sources of errors in diagnostic decision making. If the information that is *gathered* is deficient or unhelpful, even optimal *integration* will not produce an accurate decision. Similarly, optimal information gathering may be followed by poor or biased integration, which could still produce a nonoptimal decision. Thus, the final decision may be faulty as a result of limitations in either or both of these components.

In both experiments there were two task conditions: 1) a *partial-information* condition where physicians gathered a limited amount of additional diagnostic information and then integrated it before making a decision, and 2) a *full-information* condition where physicians received the full set of diagnostic information and had only to integrate the data before making a decision. The questions of interest centered on the extents to which the two information conditions affected: 1) what information the physicians considered most important, compared with that dictated by normative theory (i.e., Bayes' theorem); 2) the physicians' confidence in the appropriateness of the information they gathered; and 3) the accuracy of the physicians' diagnoses.

Experiment 1

METHODS

The Experimental Problem

The problem used in this study represents a simplified diagnostic task of deciding between two diagnostic hypotheses or alternatives based on the probabilistic relationship of a symptom and each disease. The form of the problem is modeled after that used by Doherty in nonmedical contexts.[16,18] An introductory paragraph asked the subjects to imagine themselves in medical practice in a remote area. The problem described a patient manifesting two symptoms, both of which were compatible with two different diseases that occurred with equal frequencies in the population (i.e., equal disease base rates). Additional information was available via a single "long-distance telephone call" to a specialty clinic outside the area.

The diagnostic information for the problem was presented in a 2 × 2 matrix (fig. 1). Each cell contained the conditional probability of a specific symptom given the presence of a particular disease, disease A (D_a) or disease B (D_b). Abstract diseases were used to minimize the influence of the subjects' knowledge base and prior medical experience. The subjects were given one of these four conditional probabilities (e.g., the likelihood that the patient would have leg pains given that he or she had disease B) and were asked to indicate which *one* additional piece of information they would request via their "telephone call."

The optimal solution for this type of problem is the application of Bayes' theorem (equation 1), which calculates the ratio of the posttest (or posterior) probabilities of the two diseases from the product of the disease base rates and the conditional probabilities of a specific symptom given each disease. The result of equation 1, $P(D_a|S)/P(D_b|S)$, is the posterior odds comparing the relative probabilities of the two disease possibilities given the presence of symptom S (leg pains, in this instance). This ratio is the product of the prior odds (the ratio of the base-rates or prevalences of the two diseases), $P(D_a)/P(D_b)$, and the likelihood ratio, $P(S|D_a)/P(S|D_b)$ (the ratio of the probabilities of occurrence of the symptom when each disease is present).

$$\frac{P(D_a|S)}{P(D_b|S)} = \frac{P(S|D_a)}{P(S|D_b)} \times \frac{P(D_a)}{P(D_b)} \quad (1)$$

Bayes' theorem has two implications for solving these types of problems; one for information gathering, the other for information integration. The most useful information to gather in figure 1, according to Bayes' theorem, is the likelihood of leg pains given disease A (the lower left cell of the matrix). This is the one piece of information needed to solve Bayes' theorem, given the information about the likelihood of leg pains given disease B. The disease base rates are given in the description of the problem as being equal, which means that the $P(D_a)/P(D_b)$ term equals 1 and does not alter the posterior probabilities. The information about cough, in the top two cells, does not fit into equation 1, is therefore of no real diagnostic value given the constraints of this problem, and has been called "pseudodiagnostic."[16,18–20,23]

In terms of information *integration*, the relevant conditional probabilities must be combined with the base-rate information to provide posterior probabilities for each disease. If the necessary conditional probability, P(Leg Pains|Disease A), is not available, the posterior probabilities (odds) cannot be determined because Bayes' theorem cannot be used. In this case, the optimal diagnostic decision would be to rely only on the base-rates of the diseases. Notice, however, that even if the correct information is available, it is still possible to integrate it in ways that violate Bayes' theorem, such as by ignoring the base rates or by inappropriately adjusting the conditional probabilities to produce posterior probabilities.

Subjects and Procedure

A within-subjects repeated-measures design was used in which all house officers ($n = 120$) taking a required basic life support course early in the first year of their residency training at the University of Michigan Medical School received a research instrument. This instrument contained both the partial-information condition and the full-information condition versions of the problem, along with two other problems that were not part of the current study. In the partial-information problem, the likelihood that the patient would have leg pains given the presence of disease B (58%) was left uncovered (left side of fig. 1). The physicians's first task was to "call" the specialty clinic (by peeling off a opaque sticker) to obtain *only one* of the three remaining probability values. The three alternatives consisted of the likelihood of leg pains given disease A (the optimal choice), the likelihood of cough given disease A (a nonoptimal choice), and the likelihood of cough given disease B (also a nonoptimal choice).

The full-information problem was identical to the first in wording and probabilistic information. In this problem, however, all the probabilities were uncovered and available to the physician (right side of fig. 1). As in the first problem, the subjects received the likelihood of leg pains given disease B in the description of the case and were then asked to indicate which one of the three remaining conditional probabilities they would seek in their "telephone call." Unlike the first problem, however, the information they had available for further integration was not constrained by the information they requested in their call.

For both problems, after making a "call," the subjects indicated how confident they were that they had chosen the most information of the three "calls" on a scale ranging from 1 = I am only guessing to 10 = I am absolutely sure. The physicians then diagnosed the patient as having either disease A or B.

Contingency analyses (McNemar test for symmetry and Pearson χ^2) were used to analyze physicians' information selections and disease diagnoses on the two problems. Analysis of variance was used to compare confidence ratings.

RESULTS

A total of 105 physicians completed the experimental problems. The appropriateness of the information the physicians selected as most important did not differ between the partial- versus full-information problems (McNemar test, $\chi^2(1,103) = 0.03$, ns, table 1). In both versions, 58.7% selected the optimal information. This was better than chance (33.3%) but hardly perfect. More physicians selected the optimal information in both problems (40.4%) than consistently selected the nonoptimal information (23.1%). About 37% of the physicians made inconsistent choices over the two problems (divided equally between those making first optimal and then nonoptimal choices and those

Table 1 • Comparison of 104 Physicians' Datum Choices in the Partial- and Full-information Problems*

	Partial-information Problem Datum Choice		
	Optimal	Nonoptimal	Total
Full-information problem datum choice			
Optimal	42 (40.4%)	19 (18.3%)	61 (58.7%)
Nonoptimal	19 (18.3%)	24 (23.1%)	43 (41.3%)
Total	61 (58.7%)	43 (41.3%)	104†

* McNemar χ^2 (1,103) = 0.03, not significant.

† One case was eliminated from this analysis due to the subject's error in completing this part of the problem.

Table 2 • Percentages (n) of 104 Physicians' Diagnostic Decisions Favoring Disease B for the Partial-information Problem

	n	Percentage Diagnoses of Disease B: Observed	Percentage Diagnoses of Disease B: Bayes' theorem	z	Significance of Difference
Optimal datum selection	62	95.2% (59)	100%	1.77	$p < 0.08$
Nonoptimal datum selection	43	72.1% (31)	50%	3.23	$p < 0.002$

making first nonoptimal and then optimal choices); there was no tendency to perform better on one problem than the other. The physicians' confidence in the informativeness of their selections was significantly lower in the partial information problem than in the full information problem [mean (SD) = 5.2 (5.1) vs 6.3 (5.0), respectively, $F(1,104) = 25.50$, $p < 0.0001$).

Once they had selected the information, the physicians then needed to integrate it in order to make a diagnostic choice. The quality of their diagnoses, like the quality of their information selections, can be assessed by comparison with the diagnosis indicated by applying Bayes' theorem to the information that the physicians had available. In the partial-information problem, disease B is the most probable diagnosis if the physician selects the optimal information. If, however, the physician selects one of the nonoptimal probabilities, the available information cannot be used to form a likelihood ratio and thereby fully apply Bayes' theorem. The normatively optimal decision in this case would be to rely on the base rates of the two diseases. Because the base rates are equal, and the diagnostic choices are binary (disease A or disease B), the distribution of the physicians' diagnoses should be evenly divided between the two options in the partial-information problem when they select nonoptimal information. In the full-information problem, all the information was available, regardless of what the physician selected. In this problem, Bayes' theorem indicates that disease B is the more likely diagnosis.

In the partial-information problem, physicians who selected optimal information also did quite well in identifying the optimal diagnosis (92.5%, table 2). However, those who selected nonoptimal information for their consultation "call" more often selected disease B than would be expected by applying Bayes' theorem to the same information (72.1% observed vs 50% expected, $p < 0.002$, table 2). In the full-information problem, 98.0% of the physicians selected the most probable disease (disease B), even though they might have selected a nonoptimal datum for their "call." This was not significantly different from that indicated by Bayes' theorem.

DISCUSSION

In summary, there was no difference between the percentages of physicians who selected the datum required for applying Bayes' theorem when they had a limited set of diagnostic information available compared with when they had all the information available. In both problems, over half of the physicians selected the optimal datum, while almost 40% chose nonoptimal information. While the availability of all the diagnostic information did not have an impact on these physicians' datum choices, those who made nonoptimal choices were substantially more confident of the appropriateness of their choices when they could see all the information than when they could not. While it is not certain why this might be, it is quite likely that seeing the other values, including the optimal information, enabled them to justify their choices based on the contrasting sizes of the conditional probabilities.

In comparison with the fairly high incidence of errors in information gathering, these physicians appeared to do better in integrating the information in determining a diagnostic choice. When their information was limited to what they actually selected (the partial-information problem), the physicians who made an optimal selection of information used it appropriately to make diagnoses in keeping with Bayes' theorem. However, those who selected nonoptimal data tended not to follow Bayes' theorem, more often selecting disease B than they normatively "should" have. When they had all the information available (the full-information problem), 98% of the physicians correctly diagnosed the patient's problem, regardless of whether they had identified the optimal piece of information as most important.

The explanation and interpretation of these findings are open to some question, however. The significantly higher rate of selecting disease B may have simply been due, in part, to the probability values the physicians saw when they made nonoptimal information selections; the 58% for disease B (given) was higher than either probability in the nonoptimal cells (24% and 43%). This simple contrast may have led physicians to prefer disease B as a diagnosis because it had a higher number attached to it, even if that number was normatively interpretable in that context. Also, the highly accurate diagnostic performance in the full-information problem may have been due in some part to the fact that the subjects had worked on that problem already in the partial-information condition. The strength of this possible explanation is weakened, however, by the fact that the physicians did no better in identifying optimal information in the full-information problem even though they previously had worked on the partial-information version.

These uncertainties point to several limitations in this study that constrain interpretation of the results.

The fact that each physician completed both problems raises questions about the independence of the performances on the two problems. Also, the problems were identical except for the format and were presented in the same order for all subjects. This raises questions about whether the physicians learned or realized the optimal selection of gathering information by doing the first problem and then transferring that realization to the second problem. The data do not support this idea, however. There was no increase in the quality of the data selections overall. Also, the numbers of physicians who went from an optimal selection on the first problem to a nonoptimal selection on the second and vice versa were equal.

The experimental problem also may have been unduly simplified by making the base rates of the two diseases equal, which means they had no differential influence on the relative probabilities of the diagnoses. We can therefore make no statement about whether or not the subjects paid any attention to the base rates or used them in their diagnostic decisions.

In an effort to address some of these concerns and further clarify the importance of information gathering vs information integration in decision making, we designed a second study which 1) used a between-subjects design for comparing the full- vs partial-information conditions; 2) contained multiple problems with various base rates, diagnostic alternatives, and symptoms; 3) modified the wording of the problems slightly and eliminated the initial provision of one of the conditional probabilities; and 4) asked the physicians to estimate the probability of their diagnosis as well as make a dichotomous diagnostic choice.

Experiment 2

METHODS

Three diagnostic problems were designed that were similar in format to those in experiment 1. The three problems differed in 1) the diseases and symptoms used, 2) the values of the conditional probabilities contained in the cells of the matrix, and 3) the base rates of the two diseases. The ratios of the base rates in the problems were 1:1 (i.e., equal); 2:1 (one disease twice as likely as the other); and 5:1 (one disease five times as likely as the other). All diseases were abstract, e.g., disease H.

An introductory paragraph asked the subjects to imagine themselves practicing in a clinic that had a computerized database to aid them in making diagnoses. The database could provide them with information about prior clinic patients, the diseases they had, and the accompanying symptoms. The subjects selected two of the four cells from the matrix reflecting the information they thought would be most helpful in making a diagnosis. They then indicated how confident they were that the two cells they had selected were indeed the most useful on a scale ranging from 0 (I was only guessing) to 10 (I'm absolutely sure I picked the best information). Following this, they selected one of the two diagnostic candidates as the more likely diagnosis and recorded the probabilities they assigned to each candidate. The instructions for the problem specified that these probability estimates should sum to 100%.

The two versions of the research instrument contained all three of the problems in randomized order. In the full-information version, the conditional probabilities of each symptom given each disease (i.e., all four cells) were visible in each of the three problems. In the partial-information version, the cell probabilities were printed in an invisible ink which required a special chemical marker to develop the information. In the full-information version, the physicians indicated their information selections by circling two cells. In the partial-information version, they selected information by using the latent-image marking pen to develop the information in two cells. The only difference between the two versions was in the amount of information available for making diagnostic judgments. In the full-information version all the data were available, while in the partial-information version only the information from the two selected cells was available. Thus, the partial-information version introduced constraints on those physicians' diagnostic judgments due to the quality of the information they selected. There were no such constraints in the full-information version.

The two versions of the research instruments were randomly assigned to 108 physicians participating in two continuing medical education courses at the University of Michigan Medical School. The physicians' performances over the three problems were summarized in the following dependent variables:

1. The percentages of problems in which each physician selected optimal and nonoptimal pairs of cells (from a normative Bayesian perspective). These percentages were based on the number of problems completed.

2. The average rating of how confident each physician was that he or she had selected the most useful information. This average was calculated for each individual over the problems completed, and separately for problems in which he or she made an optimal selection and those in which he or she made a nonoptimal selection. Thus, each subject could have three average confidence ratings, one over all problems, the second for problems with optimal selections, and the third for problems with nonoptimal selections.

3. The quality of the physician's diagnostic decisions was compared with the normative Baye-

sian solution based on the data that were available to the physician in that problem. This performance was summarized for each physician as the percentage of problems in which he or she made the optimal diagnosis.

4. The accuracy of the probability estimates also was compared with the Bayesian solution based on the available information. Accuracy was determined by the absolute deviation of the physicians' estimates from the Bayesian estimate averaged over all the problems. The absolute deviation was used to prevent over- and underestimates from canceling each other out.

RESULTS

There was no difference between the two conditions in the appropriateness of the information the physicians selected as most important. In both conditions, physicians selected the optimal pair of cells in about 25% of the cases (mean = 25.5% in the full-information condition and 23.6% in the partial-information condition, $t = 0.34$, $p < 0.74$).

The confidence the physicians had in the usefulness of the information they had selected was significantly higher in the full- than in the partial-information condition [mean (SD) = 5.3 (2.7) vs 3.8 (2.1), respectively; $F(1,105) = 9.88$, $p < 0.002$]. It is noteworthy that in either condition, the confidence the physicians had in their information choices was unaffected by the optimality of those choices; they were just as confident when they made pseudodiagnostic choices as when they made optimal choices ($t = 1.09$ and 0.27, ns for the full- and partial-information conditions, respectively).

Regardless of the quality of the diagnostic information the physicians selected, their actual diagnoses made fairly accurate use of whatever information was available. On the average, physicians in the full-information condition made optimal diagnoses in 66.7% of the problems, while physicians in the partial-information condition made optimal diagnoses 61.8% of the time ($t = 0.80$, $p < 0.43$). Notice again that the definition of the optimal diagnosis is defined by applying Bayes' theorem to the information that the physician had available for that problem. In the full-information condition, the diagnosis was the same for everyone, regardless of the data they had selected in the previous step. In the partial-information condition, the most likely diagnosis might be quite different for those who had selected optimal vs nonoptimal data in the previous step. This is because those who selected nonoptimal information should, according to Bayes' theorem, base their diagnosis on the base rates of the two diseases. In contrast, optimal information selection provides information that may alter the base-rate probabilities to provide a different diagnosis as most likely. This analysis examines how well the physicians use the information they have, rather than how good they are at selecting the "best" information.

The accuracy of the physicians' probability estimates of the diagnostic alternatives also showed no differences between the two conditions. The average absolute deviation of the physicians' probability estimates from that obtained by applying Bayes' theorem to the data available was 16.5% (SD = 7.3) in the full-information condition, compared with 18.5% (10.2) in the partial-information condition ($t = 1.09$, $p < 0.29$).

DISCUSSION

As in experiment 1, the two experimental conditions did not affect the frequency of selecting optimal information in these diagnostic problems; in both the full- and the partial-information conditions physicians selected optimal information in an average of 23% of the cases. Although the quality of information gathered did not vary with the condition, the confidence the physicians had in their selections did. They were much more sure that they had selected the best set of information available when they could see all the alternatives than when they could not, regardless of whether they actually selected optimal information.

Although the physicians *gathered* information in accordance with Bayes' theorem in only 23% of the problems, they *used* the information they had available to make a diagnosis in keeping with Bayes' theorem in over 60% of the cases. To some extent, this may reflect the difference in chance rates of occurrence for the two events (33% for selecting optimal information vs 50% for making the "correct" diagnosis). However, it also substantiates the findings of experiment 1, which indicated a high percentage of physicians making the correct, normative diagnosis.

Conclusion

The results of both experiments suggest that these physicians were better at making normatively optimal diagnostic decisions when they had optimal information than they were at selecting this optimal information. This basic conclusion echoes the observation made by Beyth-Marom and Fischhoff[22] that people generally show a qualitative understanding of diagnosticity if information is selected and organized for them, but seem to have much more difficulty if they have to select the information themselves. These findings suggest that faulty diagnostic decisions may more often result from difficulties people have in knowing what is useful, diagnostically meaningful information, rather than from difficulties in combining, integrating, and organizing available information to make categorical decisions, at least in the relatively simple tasks used in the study.

Several qualifications need to be placed on such a conclusion drawn from the present studies. For one, the diagnostic task was quite simple, being limited to only two diagnostic alternatives and two symptoms. While the criterion for an accurate diagnosis was the most likely disease based on Bayes' theorem, there are numerous other factors operating in real-world diagnostic situations that will influence what the *correct* diagnostic choice might be. Additionally, the physicians were given the diagnostic alternatives a priori rather than having to generate them from the clinical information, as is more typically the case. Whether these results would be replicated in more complex tasks containing more information and possible diagnoses remains a question for future study.

Another significant issue in this study was the influence of increasing expertise in performance in this task. Prior research[24–26] has shown that novices and experts use hypotheses and information in different ways to arrive at a diagnosis. These differences are attributable to differences in the breadth and organization of novice and expert knowledge bases. The task in the present studies intentionally sought to avoid influences from such differences in knowledge by using abstract diseases (i.e., disease A) to study general decision-making processes independent of content knowledge. Although there were no clear substantive differences in the patterns of results obtained in experiment 1, in which the subjects were first-year house officers, and experiment 2, with practicing clinicians of varying levels of experience, the differences in the problems and designs of the two experiments do not allow conclusive statements about the role of expertise. Further work needs to be directed toward understanding the extent to which level of expertise influences performances on similar tasks set in the context of particular content areas.

If the conclusion is indeed valid, viz, that information gathering and selection are more problematic than information integration and use, it in turn suggests that educational interventions be targeted at improving the procedures physicians use in gathering information. One such effort provided some encouraging evidence that a fairly simple training sessions could greatly improve data selection in the types of problem used in the present research.[23,27] How long-lasting and how generalizable such educational efforts might be is not known.

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