ACADEMIC PRESS

Journal of Biomedical Informatics 35 (2002) 52–75

Journal of Biomedical Informatics

www.academicpress.com

Methodological Review

Emerging paradigms of cognition in medical decision-making

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Received 7 January 2002

Abstract

The limitations of the classical or traditional paradigm of decision research are increasingly apparent, even though there has been a substantial body of empirical research on medical decision-making over the past 40 years. As decision-support technology continues to proliferate in medical settings, it is imperative that "basic science" decision research develop a broader-based and more valid foundation for the study of medical decision-making as it occurs in the natural setting. This paper critically reviews both traditional and recent approaches to medical decision making, considering the integration of problem-solving and decision-making research paradigms, the role of conceptual knowledge in decision-making, and the emerging paradigm of naturalistic decision-making. We also provide an examination of technology-mediated decision-making. Expanding the scope of decision research will better enable us to understand optimal decision processes, suitable coping mechanisms under suboptimal conditions, the development of expertise in decision-making, and ways in which decision-support technology can successfully mediate decision processes. © 2002 Elsevier Science (USA). All rights reserved.

Keywords: Medical decision-making; Cognition; Naturalistic problem solving; Conceptual knowledge; Diagnostic reasoning; Heuristics; Biases; Distributed cognition; Research paradigms

1. Introduction

In light of an increasing awareness of errors in medicine and of the importance of decision support in clinical systems, the study of medical decision making[1] is an increasingly influential area of research in medical informatics. There is a growing awareness that physicians' decisions too often result in suboptimal outcomes, which sometimes lead to adverse consequences for a patient. In general, decision research in medicine has focused on two sets of interdependent objectives: (1) understanding how physicians, other healthcare professionals, and patients make decisions in experimental and "real-world" settings and (2) devising ways to facilitate the decision process, including the development of technologies ranging from paper-based guidelines to computer-assisted decision-support technologies and training in decision methods. In an important sense, understanding decision processes can provide a meaningful framework for ameliorating or facilitating decision-making in practice. This paper is principally concerned with empirical decision research devoted to characterizing the decision processes in medicine. Although medical decision-making research has been an active area of inquiry for many years, we believe progress has been less than satisfactory in both understanding the decision process and conceiving of methods, both instructional and technologic, for improving this process.

This paper presents a review of new directions in decision-making research. These relatively new approaches, as exemplified by naturalistic decision-making research, have expanded the scope of "traditional decision research."[2] Following Beach and Lipshitz [1], the tradi-

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[1] We use the terms decision-making and medical decision-making both to characterize a cognitive process involving decisions and to name a field of research with particular theoretical and methodological approaches.

[2] The term "traditional" is used to designate a large and heterogeneous body of descriptive and prescriptive research that uses normative models (e.g., subjective expected utility, Bayesian) as points of reference. This category greatly simplifies some significant differences in perspectives and approaches. "Classical decision theory" is sometimes used to reference the same set of ideas and bodies of work.

PII: S1532-0464(02)00009-6

tional or "classical" decision theory refers to the collection of "axiomatic models of uncertainty and risk (probability theory, including Bayesian theory) and utility (including multi-attribute utility theory), that prescribe the optimal choice of an option from an array of options, where optimality is defined by underlying models and the choice is dictated by an explicit rule, usually some variation of maximization of (subjective) expected utility" (p. 21).

Some have argued that the new approaches are inconsistent with traditional decision research, suggesting that such investigation necessitates a new and more *ecologically* valid[3] paradigm for decision research [2] Although we view some of the criticisms as compelling, we also acknowledge that conventional decision research has much to offer. There is a need to find common ground such that we can better understand and modify suboptimal decision practices. The objective of this paper is to review critically both traditional and recent approaches to medical decision-making. Our primary focus is on descriptive research concerned with the characterization of decision-making behavior rather than prescriptive research designed to inform clinicians' decision practices. To foreshadow our conclusions, we argue for a need to reconstitute the "basic science" framework underlying decision-making research and applications.

Although we focus on cognitive issues in the study of medical decision-making, this paper is not intended to be a comprehensive review of the area. The paper largely focuses on understanding the decision-making processes of physicians and other participants in the healthcare process. In addition, the emphasis is on conceptual issues rather than methodological ones.

The paper is organized into six sections. First, we present some fundamental ideas underlying traditional decision-making research, followed by a brief review of empirical research on medical decision-making. In subsequent sections, we discuss developments in cognitive perspectives on decision research, which includes an integration of problem-solving and decision-making research paradigms, the role of conceptual knowledge in decision-making, the emerging paradigm of naturalistic decision-making, and finally, an examination of technology-mediated decision-making. The last four perspectives challenge some of the fundamental presuppositions of the "traditional" view of decision-making. This paper represents an elaboration or extension of our published primer on medical cognition [3] and is similarly built around a set of claims. Claims are hypotheses about the decision-making process that have substantial support in the literature. The central argument in this paper is that the empirical/descriptive research program in medical decision-making has been too narrowly conceived. As currently constituted, the traditional program in decision research cannot adequately inform the development and implementation of effective decision-support systems and the practice of evidence-based medicine. In our view, some of the newer directions in decision research can contribute to a more robust framework for understanding and modifying the medical decision-making process.

[3] "Ecological validity" refers to whether an experimental approach or construct adequately mirrors conditions in naturalistic settings.

2. Decision research

Decision making is central to all human intellectual activity. It is not excessive to suggest that decision-making is nearly synonymous with thinking. Decision making has been an active subject of psychological inquiry, since the beginning of experimental psychology. There have been thousands of experiments, journal articles, and countless anthologies devoted to the subject. However, this subject is not uniquely the province of psychology. Economics, law, political science, organizational science, and medical informatics (to name but a few disciplines) are focally involved in the study of decision-making; each with a voluminous bibliography devoted to the topic. The "science" of decision making has given rise to cottage industries and numerous related endeavors designed to influence our decision choices towards both noble pursuits (e.g., improving therapy for diabetic patients) and less virtuous ends (e.g., selling of tobacco products). There are clearly many people who have vested interests in understanding how human beings make decisions. Although experts across domains, including healthcare professionals, are generally highly proficient decision-makers, their erroneous decisions have become the source of considerable public scrutiny. In industries such as aviation and aerospace, faulty decisions by both designers and practitioners have been singled out as the cause for several errors. The Institute of Medicine's recent report [4] also acknowledges that certain errors are a result of flawed decision processes either by a single individual or by a team of healthcare workers.

Given that the landscape is vast, how can we possibly make progress on this complex endeavor? We may start by provisionally putting forth a set of propositions that are elaborated further in subsequent sections. Decisions involve choosing a course of action among a set of options with the intent of achieving a goal. According to Hastie [5], a decision involves three components: (a) choice options and courses of actions; (b) beliefs about objective states, processes, and events in the world, including outcomes states and means to achieve them; and (c) "desires, values or utilities that describe the consequences associated with the outcomes of each action-event combination." Good decisions are those that effectively choose means that are available in a given situation to achieve as well as possible the individual's goals.

The question of what constitutes a good decision suggests that we can specify criteria or evaluative standards for decision-making [6]. This is a framing assumption of the normative programs of research [7], also known as rational choice theories or rational decision-making. Prescriptive models flow from normative standards in specifying how decisions ought to be made. Descriptive models are characterizations of how physicians (or others) actually make decisions. Like most cognitive scientists, we undertake research that largely adheres to a descriptive approach in that we are interested in understanding how healthcare professionals, patients, and lay people make health-related decisions. However, this is not an ivory tower pursuit. We believe that research on understanding decisions and decision makers can contribute substantially to the development and implementation of clinical-practice guidelines, the design of electronic medical records, and clinical training.

Medical decision-making has been the subject of formal research and related applications for nearly half a century. There is a professional and academic society (the Society for Medical Decision Making), annual meetings, and a dedicated journal (Sage Publications: *Medical Decision Making*) devoted to understanding and improving decision practices. There is also a reasonably well-established paradigm for studying medical decision-making processes grounded in the normative comparative approach (see next section). The *stereotypical* version of the medical decision maker suggests a coolly dispassionate, hyper-rational physician systematically considering well-defined options (i.e., therapeutic choices or diagnostic alternatives) on the basis of a careful weighing of the evidence. Equally common is his or her decidedly less competent colleague—a fallible reasoner—subject to biases and particularly deficient in the application of probability theory to decision problems. These shortcomings frequently result in faulty decision practices.

Traditional empirical research on decision-making focuses on an individual's decisions in a controlled laboratory setting. There have been several research approaches to the psychological study of decisions. Problem-solving research [8,9] has also influenced the study of decision-making. As discussed in a subsequent section, problem-solving and decision-making research constitute two distinct paradigms and employ different theoretical assumptions and methodologies. Problem-solving research emphasizes the sequential process of searching for a solution path, whereas decision research focuses more on the nature of the decision outcome and how it may deviate from an acceptable normative standard. In addition, there have been several distinct approaches to decision-making research [10]. One such approach is "social judgment theory" [11], based on the pioneering work of Brunswik [12]; a second approach is "information integration theory" [13]. The most widely known and influential research program in the psychology of decision-making was Tversky and Kahneman's work on judgment under uncertainty [14]. This program, exemplified by work on heuristics and biases, had a profound influence on decision research in many disciplines.

In a "typical" decision-making study, a subject is presented with a brief decision scenario or clinical vignette (e.g., description of medical problem) and is required to select a course of action from a set of fixed alternatives. This contrasts with a normative model, based on expected utility theory or probability theory, indicating "optimal" choices under conditions of uncertainty [15]. Uncertainty reflects a judgment of the likelihood of a given event to occur in a particular situation (e.g., a patient's adverse reaction to medication) and is often expressed in terms of probabilities. Most studies emphasize how the decision maker deviates from normative standards. This is in contrast with a descriptive approach of decision making in which the objective is to characterize a decision process or approach in which expert performance serves as the gold standard of performance. These approaches are discussed in subsequent sections of this paper.

Decision research has greatly expanded in the last 20 years. Consider the following scenarios:

(a) A 36-year-old woman has just been informed that she has breast cancer. She must decide whether to undergo a radical surgical intervention that is associated with a very good survival rate or a less appearance-altering operation that carries with a greater concomitant risk of mortality.
(b) A HIV-positive patient who had previously strictly adhered to a complex combination anti-retroviral treatment regimen and schedule has decided to stop taking his medications for a short while because the side effects are adversely affecting his lifestyle.
(c) ICD-10 specifies two categories of causes for heart failure (congestive heart failure and left ventricular heart failure) as well as a residual *unspecified category*. The listing expressly excludes *heart failure secondary to obstetric surgery* or *secondary to renal disease*.
(d) A physician studies a decision flowchart embedded in a clinical practice guideline to prescribe anti-hypertensive medications to a patient with a complex medical history.
(e) An electronic medical record system, which employs an elaborated medical vocabulary and highly structured interface, is found to affect systematically the diagnostic and therapeutic practices in a diabetic clinic.
(f) A team of healthcare professionals in an intensive care unit engages in an animated debate about

whether to wean a patient off a ventilator. The patient, who had been previously progressing satisfactorily, had a difficult night and her respiratory status was hard to gauge.

(g) A laparoscopic gallbladder removal surgery is proceeding normally up until a point when the surgeon is having difficulty locating the bile duct. Continuing the procedure runs the risk of serious injury to the patient. The surgeon must decide whether to proceed or to convert the operation to open surgery.

Scenarios (a) and (b) highlight the role of patients as decision makers. They also serve to illustrate that decision-making is not merely an analytic or dispassionate process, but often involves an affective component [16]. It is reasonable to assert that, to varying extents, all healthcare decisions, whether made by physicians or patients, have an affective quality to them. It is of course possible to model emotionally laden beliefs using subjective utilities. However, decisions carry meaning for the participants in ways that are not easily expressible in the common currency of utility [17]. The third scenario (c) indicates that developing a nomenclature can be construed as a particular kind of medical decision. ICD-10 is designed to both reflect the decision practices of physicians as well as to shape them. Scenarios (d) and (e) implicate technology in the decision process. Many, if not most, medical decisions are mediated by technology.[4] It is our view that technology does not merely support or enhance the decision processes, but fundamentally transforms it. The teamwork scenario (f) demonstrates that many medical decisions are distributed over a number of individuals with different spheres of expertise. Even if a single individual ultimately decides on a final course of action, others are critically involved in the process. The ICU example also illustrates that in everyday situations, decisions are embedded in a broader context and are part of a decision-action cycle that is affected by monitoring and feedback rather than a single judgment [18]. In addition, the cognitive properties of a group may differ from those of individuals [19]. We expand on these themes in the section on naturalistic decision-making below. Scenario (g) shows that uncertainty changes over time and that complex perceptual-motor judgment is not easily reducible to simple principles.

3. Psychological dimensions of decision-making

Empirical research on decision-making can be traced back to the 1940s and 50s [20]. Much of this work was inspired by von Neumann and Morgenstern's theory of games [7], within which social scientists in several disciplines advanced the systematic study of decision-making by developing abstract theoretical models and conducting empirical studies. Scholars in many social science disciplines, including economics, business, psychology, sociology, and political science devoted considerable effort to applying such models and refining them to investigate diverse phenomena and to develop related applications.

Arguably most of this research was influenced in some way or by the normative or rational decision approaches, the normative character of which is predicated on the use of various mathematical formalisms that are supposed to represent a standard of rationality and rational decisions. Typically, normative theories of decision-making are based on two main types of models. The first type of models makes use of expected utility (EU) and subjective expected utility (SEU) as criteria for "rationality." The idea behind these models is that in making decisions one should maximize one's gain, which is calculated as the ratio of chance taken by amount of payoff. The second type of model makes use of the notion of conditional probability, as expressed in the subjectivist, personalist, or Bayesian perspective (the Laplace–Bayes theorem). Two attractive aspects of these approaches are that they offer a standard to compare or to improve actual human decision-making and that they provide apparently well-defined mathematical models of rational decisions. Most subsequent decision-making research has been influenced by these approaches, especially in psychology and the behavioral sciences.

3.1. The heuristics and biases program

Claim 1. *Heuristics and biases significantly impact the process of decision-making and have been well documented in the context of health-related decisions.*

In keeping with the rational choice approaches, much of the research on the psychology of decision-making contrasts observed decision-making to a normative standard (e.g., SEU or Bayesian models). Systematic deviations from normative standards are seen as decision biases. According to Chapman and Elstein [21], biases are important for two reasons: (1) they offer insights into the cognitive processes underlying decision-making and (2) they may be suggestive of areas where improvement is needed. Improved decision processes can result in better patient care and health outcomes.

By the late 1960s, psychologists had amassed a considerable body of research documenting numerous decision-making and reasoning anomalies in individuals [20]. It was apparent that people are not skilled Bayesians and that their probability judgments deviated from the normative standards in systematic ways. However, a psychologically adequate explanation for individuals'

[4] Technology is used in this paper to refer to both computer-mediated technology and other artifacts (e.g., charts, paper guidelines) that are used to achieve similar ends.

biased judgments was entirely lacking. Kahneman and Tversky's (e.g., [22]) seminal studies and theories revolutionized the field of decision research. Their research is exemplified by the following quotation:

> How do people assess the probability of an uncertain event or the value of an uncertain quantity? This paper shows that people rely on a limited number of heuristic principles, which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. In general, these heuristics are quite useful, but sometimes they lead to severe and systematic errors [14].

Sometimes judgments are erroneous because we attend to variables that we should ignore and, alternatively, ignore variables that are worthy of our attention [6]. Misleading heuristics that subjects use to generate inferences and biases contribute to faulty judgments. Tversky and Kahneman argued that subjects typically fail to base judgments on perceptions of likelihood, but estimate the probability of an event from a population according to the representativeness of the sample. The salient features of the problem and its similarity to salient aspects of the population appear to be a guiding force in people's estimation. This is better illustrated in the context of an example. Consider the following classic problem [23]:

> A cab was involved in a hit and run accident at night. Two cab companies, the Green and Blue, operate in the city. You are given the following data.

(a) 85% of the cabs in the city are Green and 15% are Blue.
(b) A witness identified the cab as Blue. The court tested the reliability of the witness under the same circumstances that existed on the night of the accident and concluded that the witness correctly identified each of the two colors 80% of the time and failed 20% of the time.

What is the probability that the cab involved in the accident was Blue rather than Green?

Bayes' Theorem tells us:

$$p(H|D) = \frac{p(D|H) \ * \ p(H)}{p(D|H) \ * \ p(H) + p(D| \sim H) \ * \ p(\sim H)}.$$

In this formulation, $p(H|D)$ is the probability of H (the hypothesis that the cab was Blue) given D (the datum that the witness reported the car was Blue). Thus, $p(H|D)$ is the posterior probability of H after D is known, $p(H)$ is the prior probability that the car is Blue (stated to be 15%), $p(D|H)$ is the probability of D given H (that is, the chance the witness will report the car to be Blue if it is really Blue, stated to be 0.8), $p(D| \sim H)$ is the chance the witness will report the car to be Blue if it is really Green (stated to be 0.2), and $p(\sim H)$ is the prior probability of not being H (in this case, the proportion of cabs that are Green rather than Blue, or 85%). Substituting into Bayes' Theorem, we calculate the probability that the cab is Blue rather than Green, when the witness says it is Blue, as:

$$p(H|D) = \frac{.80 \ * \ .15}{.80 \ * \ .15 + .20 \ * \ .85} = .41$$

Experience in this and many other similar examples show that many respondents, when presented with this question, are heavily swayed by the information on the witness' accuracy (or the most salient aspect of the event) and suggest that the probability that the cab is Blue is 80%. Almost all respondents provide estimates in excess of 50%, even though the correct answer is 41%. They fail to consider adequately the base rate of Blue cabs in the city (15%). There have been similar findings in the domain of medical decision-making, which is striking, given the frequency with which similar issues arise in the interpretation of test results. Clinicians often overestimate the impact of a positive test, failing to appreciate the importance of the base rate (prevalence) of the disease they are considering. Consider the following example [24]:

Estimate the probability that a woman has breast cancer given that she has a positive mammogram on the basis of the following information:

(a) The probability that a patient has breast cancer is 1%. (This provides the prior probability.)
(b) If the patient has breast cancer, the probability that the radiologist will correctly diagnose it is 80%. (This provides the sensitivity or hit rate.)
(c) If the patient has a benign lesion (no breast cancer), the probability that the radiologist will misdiagnose it is 9.6%. (This provides the false positive rate.)

According to Bayes' rule, the probability that this patient has breast cancer is about 8%. Eddy found that 95 out of 100 physicians estimated the probability of breast cancer after a positive mammogram to be around 75%. The test result and its sensitivity seem to be the most salient feature and the base rate is largely ignored. The results are analogous to those found in the accident scenario and many other similarly documented decision situations [25].

The two above examples illustrate the judgment under uncertainty approach pioneered by Tversky and Kahneman and widely used by the decision-making and judgment community. First, subjects are presented with a problem and their responses are compared with normative responses. The deviation between individual's responses and the normative response is explained by heuristics in which the reasoner selectively attends to certain variables or exhibits particular kinds of biases such as ignoring base rates. Biases are, more generally, violations of consistency constraints imposed by probability theory. Representativeness and availability are perhaps the most widely studied heuristics. Availability is the tendency to assess the frequency, probability, or likely causes of an event by the degree to which the instances or occurrences of the event are readily available in memory. For example, an event that is distinct, easily imagined, and specific will be more available than will an event that is unemotional in nature [17]. A physician may readily recall a vivid encounter with a patient when treating a patient whose symptoms are superficially similar, but different in important respects. This may cause a range of errors in physician's decision-making. For example, they may lend greater credibility to the likelihood of a rare disorder without a proper consideration of base rates.

Researchers have documented numerous heuristics including anchoring and adjustment, and simulation (i.e., if an individual can readily envision an event, she is more likely to assign it a higher likelihood of occurrence than an alternative) and many biases such as insensitivity to sample size, illusory correlations, overconfidence, and hindsight bias. Studies have similarly documented a wide range of biases in physicians' decision-making. In a recent review of the literature, Chapman and Elstein [21] consider 12 distinct biases. We briefly review such biases here. They fall into two broad classes: (1) biases that emerge when judging the probability of events such as possible diagnoses and treatment outcomes and (2) biases that occur in evaluating the utility of an outcome.

Hindsight bias occurs when the decision maker inflates the possibility that they would have correctly diagnosed a patient. Arkes and Harness [26] presented a clinical case to one group of physicians along with four diagnostic hypotheses. They were asked to estimate the probability of each diagnosis. In a second experiment, physicians were presented with the same case and diagnoses. However, they were also told of the correct diagnosis before estimating the probabilities. The groups differed systematically in their judgments. The group which had been told the correct diagnosis inflated its probability. The bias results in a non-normative judgment, since knowing the outcome should in theory have no effect on probability judgments. Several studies similarly documented that knowledge of an outcome focuses the decision maker's attention on case information supportive with the known hypothesis and causes them to ignore information that made alternative diagnoses plausible. Dawson and Arkes [27] argue that hindsight bias may hinder learning from cases if physicians assume that the clinical outcome is predictable. Postmortem evaluations of clinical cases are a crucial component of continuing medical education (e.g., medical grand rounds). Hindsight bias has also been cited as a reason for the misattribution of error in quality analysis [4]. Outcome bias is similar to hindsight bias in that knowledge of the outcome skews the physician's perception of a problem. Decisions are evaluated more favorably if they lead to good outcomes rather than poor ones, if they are both based on equally sound clinical judgments [21].

Hypothesis testing has been widely studied in many spheres of decision-making including medicine. Confirmation bias is perhaps the most widely documented deviation from Bayes' Theorem,[5] The bias is evidenced by the generation of a hypothesis and the subsequent search for evidence consistent with the hypothesis, often leading to the failure to consider adequately the alternative diagnostic possibilities. This may result in a less than thorough investigation with possibly adverse consequences for the patient. A desire to confirm one's preferred hypothesis may moreover contribute to increased inefficiency and costs by ordering of additional laboratory tests that will do little to revise one's opinion, providing largely redundant data[6] [21]. Furthermore, the laboratory tests may increase one's confidence in the hypothesis without increasing the accuracy.

The framing effect, a robust finding in the decision literature, suggests that alternate representations of a problem can give rise to different judgments and preferences. This form of bias has received considerable attention in decision-making research. The preference for a particular course of action is different when a problem is posed in terms of potential gain rather than potential loss, even though the underlying situation is identical. McNeil et al. [28] presented a hypothetical lung cancer decision scenario to physicians and patients. In one framing of the problem, the treatments were described in terms of survival rates, whereas in the other they were described as mortality rates. The treatment options were surgery and radiation therapy, the latter of which had an immediate higher survival (lower mortality) rate, but a lower 5-year survival rate. In the survival frame there was a clear preference for surgery, whereas in the mortality frame, the two choices were preferred equally. One possible explanation is that the positive framing leads to more risk-averse choices, while the negative framing increases risk-seeking decision-making [21].

Research on heuristics and biases has yielded a substantial body of knowledge on medical decision-making with a particular emphasis on how decision makers systematically deviate from a certain standard of rationality and coherence as defined by probability

[5] Confirmation bias has also been criticized on logical grounds [29]. The crux of the argument is that it is an example of the logical fallacy of affirming the consequent (e.g., If it rains, then it will be wet; it is wet therefore it rained). Because of this, falsification, rather than confirmation, has been proposed as the rational and only valid type of reasoning in science [30].

[6] It has been demonstrated in many different domains including medicine that experts often pursue a single hypothesis to the exclusion of alternatives. In the overwhelming majority of cases, such a strategy is well justified. However, this is a more problematic strategy when it is used by less than expert subjects. For a more thorough discussion of this issue see Patel et al. [3].

theory [31]. The prescriptive program in medical decision making, as embodied in decision analysis techniques and to some extent in evidence-based medicine, draws on similar notions of rational decision-making. In addition, training programs have endeavored to improve clinicians' decision-making acumen, even though the prescriptive program has not been an unequivocal success thus far. In the next section, we review some criticisms of traditional decision-making research. There are undoubtedly numerous reasons why many decision-support systems lead to suboptimal outcomes. However, we believe that the framing assumptions about the decision-making process are at best seriously incomplete. In the next section, we consider some of these criticisms.

3.2. The critique of the classical approach to decision-making

Claim 2. *The classical approach and research exemplified by heuristics and biases research do not adequately characterize the decision-making process.*

In the previous section, we have selectively surveyed a fraction of the voluminous body of research in the "heuristics and biases" approach to medical decision-making and judgment literature. This remarkably productive area of study has been subject to substantial criticism, both conceptual and empirical. In this section, we discuss several of these criticisms, which challenge fundamental assumptions of the traditional decision-making paradigm. The first set of criticisms is philosophical in scope in that they question the nature of the particular interpretations used to circumscribe decision problems, including whether the SEU or the Bayesian frameworks constitute appropriate frames of reference for assessing human rationality. The second set of critiques questions the ecological validity of traditional decision research. They focus on the limitations of a classical approach in meaningfully informing or influencing "real-world" decision-making.

A first philosophical criticism takes issue with whether principles from SEU or Bayesian probability theory provide the best gold standard for evaluating people's decisions. Recall that because SEU and Bayesian models are considered to be standards of optimal decision-making, decisions that deviate from the standards are seen as suboptimal or biased. However, critics argue that the term "rationality" covers many different meanings [32], only one of which (rationality as maximizing gain or economic rationality) is covered by use of the term in normative decision theories. It can be argued therefore that someone can behave rationally in other ways (e.g., ethically) while behaving irrationally in decision-theoretic terms. The implication is that individuals cannot be faulted (and their judgments are not necessarily biased or non-rational) if they make decisions in ways that contradict the SEU principles. Such critics accordingly ask whether classical decision theory's use of normative decision principles is an appropriate standard for evaluating (or facilitating) decision-making. We raise these criticisms principally because they opened the door for alternate proposals on decision-making that are arguably based on a more empirically adequate foundation [33,34].

A second philosophical criticism [35,36] has been raised against the use of Bayesian probability, specifically against the definition by some workers of probability as the strength of belief in a hypothesis. First, it can be argued that it is very restrictive (and conceptually wrong) to define probability as measuring the strength of belief because probability theory, being a branch of mathematics [37], has no factual interpretation. Similarly, in number theory, numbers do not refer to anything extra-mathematical. Those who define probabilities as measures of strength of belief make Bayesian probability a psychological theory for the simple reason that "belief" is a psychological construct (not a mathematical one). Second, even if it is maintained that the definition of probability as degree of belief holds only for the *application* of Bayesian probability to factual problems, such an interpretation is problematic. For instance, what does a physician mean when he or she says that there is a probability of 0.75 that his or her patient has cancer? What does the probability refer to? The common sense interpretation is that this probability value refers to the *chance that the patient has cancer*, which is an actual or possible objective event in the world, not a belief. From a Bayesian perspective, it is unclear to what this probability refers (to the chance of such a belief popping into the physician's head?). This is complicated because there are no scientifically acceptable procedures for assigning probabilities to beliefs, except arbitrarily. Furthermore, there is evidence to suggest that most people are not Bayesians and that their decision-making improves when probability is presented in objective terms [38,39].

Empirically based criticisms have arisen from the experimental study of decision making in a variety of domains. As described above, psychological research has compared how people actually make decisions to how they would do so under the principles of rational decision theory and found that people do not meet the normative principles. Second, researchers in economics, organizational science, and management [40–43] have criticized the normative theory based on their own theoretical and empirical studies in organizational decision-making. Two early critics of the normative approach were Maurice Allais and Herbert Simon (both Nobel laureates in Economics). Allais [40] proposed what has been known as the Allais "paradox" which showed that utility maximization principles are contradicted by effective real life decisions (most decision makers tend to be risk averse). Simon [43] showed that people are "satisficers" rather than "maximizers" [44]; that is, he showed that decisions are determined by opportunity, availability, and uncertainty about the consequences of action and personal preferences [42], and constrained by cognitive limitations. Simon introduced the concept of "bounded rationality" [43] as a challenge to the prevailing economic models of the rational decision maker. Human beings have significant information-processing limitations (e.g., attention, memory, and perceptual constraints) and need to rely on simplifying heuristics. However, these heuristics, instead of being viewed as erroneous, can be seen as powerful and effective strategies for making many everyday decisions. In this regard, the normative decision model, characterized by the systematic evaluation of multiple options or simultaneously considering several hypotheses, is simply untenable as a psychological theory. In recent years, there have been proposals of alternative normative theories and approaches (e.g., [45–48]), which do not necessitate the stringent requirements of the standard rational choice theory (i.e., utility maximization and knowledge of all the available options).

Third, when alternative interpretations of probability [36,49] are used in psychological studies of decision-making [38,39], different results are obtained. Gigerenzer [38] and Cosmides and Tooby [39] have conducted research that suggests that the Bayesian interpretation typically used by classical decision theorists may be inappropriate for both prescriptive and descriptive viewpoints. For example, in the frequentist interpretation, probabilities refer to relative frequencies over time. They argue that the frequentist interpretation more naturally reflects the way human beings reason under conditions of uncertainty. In particular, studies using similar tasks to those used Tversky and Kahneman, but expressed in frequentist terms, show that people make use of probabilistic information while showing fewer uses of heuristics and biases [39].

Fourth, descriptive decision research (as reflected in heuristics and biases) portrays decision makers as fallible reasoners whose judgments are often substantially at variance with the normative standard for rationality. A semantic issue raised by Gigerenzer [50] poses another methodological problem for this research paradigm. If there are different meanings of probability, then how are they cued in everyday language and how does this affect judgment? The findings from this work are partially predicated on how individuals interpret the meaning of probability. Gigerenzer argues that humans are evolutionarily adapted to acquire information about risks in their environment through natural sampling of event frequencies rather than in terms of sets of probabilities or percentages. He argues further that one can make perfectly rational inferences and decisions without overtly paying attention to base rates. Human beings may appear to be less competent or rational if they are asked to render judgments, based on explicit statistical information. He and his colleagues have conducted several studies that juxtapose decision problems formatted in probability terms and as natural frequencies. In one of the studies, he modified Eddy's [24] mammography problem in the following way to represent natural frequencies:

- Ten out of every 1000 women have breast cancer.
- Out of these 10 women with breast cancer, 8 will have a positive mammogram.
- Of the remaining 990 women *without* breast cancer, 99 will still have a positive mammogram.
- Imagine a sample of 100 women (age 40–50, no symptoms), who have positive mammograms in your breast cancer screening. How many do actually have breast cancer?

In the probability-formatted questions, Gigerenzer basically replicated Eddy's finding with only 8% of the physicians producing the correct Bayesian answer and with a median estimate of a 70% probability. However with the natural frequencies format, 46% of the physicians produced the correct response. The findings were similar across three other diagnostic problems. From our vantage point, the critical finding is that the representation of problem information can have a rather dramatic effect on performance and judgments of competence/incompetence. It also shows that human beings are sensitive to statistical information in their environment and that this influences their judgments under uncertainty. Decision makers are attuned to probabilities, even if they cannot articulate an accurate probability estimate.

Gigerenzer's research is not without controversy [51] and an extended discussion of his theories is beyond the scope of this paper. His work serves to highlight the adaptive (rather than the suboptimal) character of decision-making, a point that is strongly emphasized in problem-solving and naturalistic decision-making research (reviewed in subsequent sections). From a methodological point of view, his research also serves to emphasize how the cuing of language can immensely influence the understanding of probabilistic information.

Medin and Bazerman [17] argue that the heuristics and biases approach has been overly constrained by a focus on how people make mistakes at the point of decision. Research on heuristics and biases has implicitly assumed that the goal is known and the details of implementing decisions are not part of the problem. Gigerenzer [50] challenges the belief that there is a single normative standard and that most individuals make decisions that are substantially at variance with such norms.

There have been several educational initiatives intended to train physicians and other healthcare personnel in formal decision-analytic techniques to reduce the effects of biases and to improve clinical decisions [52]. As discussed previously, it is widely recognized that formal decision-making techniques have not achieved widespread acceptance in medical practice and in other professions [53]. In addition, teaching decision-analytic techniques to professionals has yielded mixed results [31]. The use of formal decision methods has often not resulted in sustained and generalizable improvements in physicians' diagnostic decisions [54] or in their therapeutic interventions [55]. There are several reasons why decision-analytic techniques may yield suboptimal results in naturalistic decision situations [56]. For example, in many cases, the decision maker may not view the task as one of choice and even when the task does involve a selection, much effort may be required to identify the alternatives available. In addition, much of the information may resist the quantification required for implementing formal decision models.

We should point out that decision analysis and decision-support systems are by no means fossilized or static enterprises. Rather they continue to be vibrant fields of research and significant advances have been made in several areas of study, including formal methods for modeling uncertainty in reasoning or decision-making [57]. We do not doubt that emerging systems can contribute to improving the process of clinical decision-making. However, our contention is that basic theoretical assumptions about decision makers and decision situations need to be reconsidered.

One of the primary reasons that training with normative decision-making models does not endure in practice is that such models are not readily applicable if the decision must be made under the kind of constraints (e.g., stress, time pressure, and limited resources) found in many natural settings [57]. It is apparent that we need a better understanding of the process of decision-making in real-world situations. Decision-making research in dynamic "real-world" environments has investigated domains ranging from fire fighting to air traffic control [58], and to healthcare domains such as anesthesiology [59], emergency nursing telephone triage [60] and, most recently, intensive care medicine [61]. We find the naturalistic critique to be quite compelling. One can argue that the impoverished situations presented to physicians in judgment studies may have no true analog in the world of clinical medicine. Although we were critical of traditional decision-making research in an earlier publication [62], we have reappraised our views on the matter and see value in the approach, despite its limitations and lack of ecological validity. We concur with Medin and Bazerman [17] who suggest that the heuristics and biases literature has yielded a fascinating catalog of human decision errors that is important for both theoretical and practical reasons.

We have reviewed a number of conceptual and empirical criticisms pertaining to classical decision research. In particular, classical authors have addressed the privileged and narrow view of rationality that permeates much of the decision research. In addition, this approach is somewhat lacking in ecological validity and this may compromise the extent to which it can inform applications in decision support. In the next section, we focus on several alternative approaches to the study of decision-making—ones that both expand the scope of decision research and offer a different take on decision-making competency.

4. Expanding the scope of decision research

This section considers areas of research that intersect with the study of decision-making, but have not been widely considered in traditional decision research. These areas have developed in parallel to the traditional investigations and collectively have contributed to a broadening of the framework of how individuals make decisions. A newly emerging framework, as discussed in this section needs: (1) to develop a more adequate descriptive account of the decision-making process, (2) to explain the adaptive as well as the suboptimal characteristics of decision makers, and (3) to recognize that decision makers are not solitary thinkers, but live in a social world thick with artifacts and populated by other agents who jointly determine the decision processes and outcomes.

There are several innovative research programs that could be discussed in this section. We have limited the discussion to issues that we view as particularly important in refining the basic sciences framework for decision-making. In addition, the areas discussed in this paper reflect problems that have been central to our own work in decision-making. The one caveat is that the reviewed research is somewhat skewed towards our own interests and our own contributions are heavily represented. The research discussed in the next two sections places emphasis on the acquisition of conceptual knowledge and on understanding the growth of decision-making acumen as a function of expertise. This work is grounded in "mainstream" information-processing theories of cognition. That research serves to emphasize dimensions of an individual's competency (e.g., domain knowledge) that influence decisions in critical ways. We also draw parallels with early research in medical artificial intelligence. These researchers were confronted with similar issues, most notably with the intractability of pure Bayesian approaches to decision-making and the brittleness of systems that lack a certain conceptual depth. In important respects, the final two sections focus on the need for a richer understanding of how decision-making occurs in real-world settings as mediated by teamwork and technologies. Although much of this work is steeped in older intellectual traditions, they are just beginning to recast decision-making in a new light—one that is substantially at variance with the classical tradition.

4.1. Problem solving and decision-making

Claim 3. *Medical decision-making research and problem-solving research employ distinct theoretical and methodological approaches drawing on diverse historical traditions to study the same phenomena and resulting in substantially different conclusions.*

Claim 4. *Decision heuristics and biases often form the basis of robust reasoning strategies by expert clinicians.*

The term medical cognition refers to studies of cognitive processes, such as perception, comprehension, reasoning, decision-making, and problem solving in medical practice itself or in tasks representative of medical practice. Much of the research in this area can be subsumed by one of the two distinct theoretical and methodological approaches: a decision-making and judgment tradition, as exemplified by the work previously described, and a problem-solving and expertise approach [62–64]. Several differences exist between these two traditions. First, problem-solving research emphasizes a characterization of cognitive processes in reasoning tasks, use of protocol-analytic techniques [65], and the development of cognitive models of performance [66], while decision-making research focuses on how and why decisions deviate from a certain standard of rationality. Second, problem-solving research views expert performance as a gold standard, whereas decision research views the expert performance as fallible and subject to the same biases and faulty decision practices as the layperson. Third, problem-solving research focuses on the role of expert knowledge organization in performance, whereas traditional decision research places less emphasis on the role of domain-specific knowledge.[7] Further differences between these two approaches are discussed in more detail in Patel et al. [3,62].

Despite these differences, there is much common ground between the two approaches, such as a focus on diagnostic and therapeutic tasks. In addition, decision-making and problem-solving research have common intellectual roots in that both were influenced by the seminal ideas of Simon's conception of bounded rationality [43] and were given a certain impetus by the emergence of cognitive science in the 1950s [66]. However, there have been numerous points of convergence and divergence in the arenas of medical cognition and medical artificial intelligence over the course of the last several decades. For the most part, researchers in medical cognition have worked either in the problem-solving or decision-making tradition, although there have been investigators (e.g., Elstein) who have made substantial contributions to both endeavors.

The guiding metaphor for decision research has been rational choice among alternatives. In problem-solving research, a key concept is search in the problem space in which a problem solver is viewed as performing an operation (either an inference or action) from a space of possible operations in moving toward a solution or goal state (e.g., diagnosis or treatment plan) [8]. The problem space places a greater emphasis on an evolving process rather than a fixed selection process. This conceptualization had an enormous impact on both cognitive science and artificial intelligence research, thus, enabling researchers to study both search strategies in human problem solvers and to develop computational models that embody them. Elstein et al. [9] were the first to employ problem-solving methods and theories to study clinical competency. Their seminal research led to the development of an elaborated model of hypothetico-deductive reasoning, which proposed that physicians reasoned by first generating and then systematically testing a set of hypotheses to account for clinical data (i.e., reasoning from hypothesis to data). This model of problem solving has had a substantial influence on studies of both medical cognition and medical education, although its generality is the subject of some controversy [67].

Medical artificial intelligence (AI) and in particular research on knowledge-based systems seeded important ideas that guided work on medical problem solving. Although AI in medicine has more openly embraced decision-analytic methods in recent years (constituting significant advances in representational and modeling techniques), most of the early work emphasized symbolic computation rather than numeric information and relied on heuristic search methods rather than Bayesian methods [68]. Purely Bayesian methods of analysis were not viewed as tractable for real-world problems for a number of reasons, most notably their inordinate demands for data and knowledge of conditional probabilities [69] and the inability to define and adequately account for conditional dependencies.

Empirical methods (e.g., protocol analysis) and theories from cognitive science were used to develop cognitive models that shaped the development of medical AI systems. For example, Gorry [70] examined the ways in which a computational model of medical problem solving compared to the actual problem-solving behavior of physicians. This analysis provided a basis for

[7] In the traditional laboratory-based decision approach, subjects are often placed in situations where prior knowledge becomes (almost) irrelevant to the kind of decision choices that one must make.

characterizing a sequential process of medical decision-making, one that differs in important respects from early diagnostic computational systems based on Bayes' theorem. Pauker et al. [71]. drew on Gorry's work and developed PIP, a program designed to take the present illness of a patient with renal disease. Several of the questions guiding this research, including the nature and organization of expert knowledge, were of central concern to both developers of medical expert systems and researchers in medical cognition. The development and refinement of the program were partially based on studies of medical problem solving. In addition, the program embodies a cognitive model of patient history taking and architectural assumptions about human memory systems. PIP employs categorical methods to derive hypotheses and both probabilistic and categorical methods for evaluating hypotheses.

Clancey's research on intelligent tutorial systems (by extending and then reconfiguring MYCIN [72] led to a highly influential cognitive model of medical problem solving [73]. In particular, he introduced key epistemological distinctions that were to have a substantial influence on the conceptualization of medical expertise. Clancey distinguished between findings, hypotheses, evidence (finding/hypotheses links), justifications (why a finding/hypothesis link is true), structure (how findings and hypotheses are related among themselves), and strategy (why a finding request comes to mind). These distinctions provided a more refined basis for characterizations of clinical reasoning strategies and medical explanation [74].

In general, researchers in medical problem solving and decision-making employed different methodologies and largely addressed different issues. However, there were notable attempts to reconcile the two traditions. Towards this end, Joseph and Patel [75] asked experts and subexperts (seasoned physicians working outside their own specialty area) to think aloud and explain clinical data on an endocrine problem presented in a sequential form, one sentence at a time (mirroring to a certain extent the interactive clinical information-gathering process). Joseph and Patel found that experts generated the correct hypothesis early in the problem and devoted the rest of the time to confirming and refining the diagnosis by explaining the rest of the patient data. Although the subexperts also generated the correct diagnosis, they took a longer time to take the final decision. The main difference appeared to be on the subexperts' difficulty in evaluating hypotheses, which resulted in the inability to eliminate incorrect alternatives. Previous research [76] showed that when experts include the correct diagnostic hypothesis in the initial hypothesis set, subsequent processing is directed at the confirmation of the hypothesis rather than at the generation of any new hypotheses. However, if the correct hypothesis is not included, then further processing includes the generation of alternate hypotheses as new data are presented.

A subsequent study, using the same experimental paradigm, compared the diagnostic decision-making process of senior physicians, cardiologists, and endocrinologists on a cardiac problem [62]. The problem described the case of a 62-year-old man who was diagnosed as having *pericardial effusion* with *pre-tamponade*, a condition in which there is a compression of the heart produced by the accumulation of fluid in the pericardial sac thereby preventing normal expansion of the heart. The results showed that experts interpreted problem data from the first few segments in terms of diagnostic hypotheses and that once the experts generated these hypotheses, they used them as a basis for evaluating data that were subsequently presented, without introducing any new hypotheses. In contrast, subexperts continued to generate new hypotheses, even after producing the correct diagnosis. From a decision-making perspective, the experts in the studies by Joseph and Patel [75] and Patel et al. [3,62] may have been guilty of a confirmation bias. As this study and many others illustrate, this bias is highly productive in most situations.

Lesgold et al. [77] documented similar findings in the domain of radiological diagnosis. They investigated the abilities of radiologists at different levels of expertise, in the interpretation of chest X-ray pictures. The results revealed that the experts were able to initially detect a general pattern of disease. This resulted in a gross anatomical localization and served to constrain the possible interpretations. Novices had a greater difficulty in focusing on the important structures and were more likely to maintain inappropriate interpretations, despite discrepant findings in the patient history. This rapid pattern recognition process is characteristic of experts in both perceptual and richly symbolic domains [78].

Kushniruk et al. [79] studied the process of intensive-care decision-making with cases that showed varying lung scan results as well as varying clinical evidence for pulmonary embolism. For example, a complex case might include a low probability lung scan and high probability clinical evidence. The subjects were asked to provide a differential diagnosis and a therapeutic and management plan. The most salient differences emerged in the complex cases, where the intermediates (residents) proposed a treatment strategy based on the evaluation of the available evidence, even when it was clearly equivocal or contradictory. In contrast, experts (critical care specialists) first stabilized the patient and deferred their decision pending the results of further tests and investigations. Experts were engaged in a process of situation assessment (for example, a careful consideration of the patient's history and events in the hospital), whereas the intermediates were much more proactive in considering treatment options and ordering further investigations.

These research studies illustrate a view of heuristics that contrasts with the view in the classical decision-making paradigm. In this research, expert strategies, which include a range of heuristics, are associated with high levels of accuracy. Experts represent the problem in such a way that recognizable patterns emerge from the data thereby minimizing extraneous search through a myriad of irrelevant information and extraneous hypotheses. Interestingly, some of the expert heuristics are suggestive of biases that would be labeled as problematic according to standards of decision research. It is certainly conceivable that a confirmation bias may occasionally prejudice the most seasoned practitioner and lead them to misdiagnose a problem. In the cases reported in many studies of expertise, however, heuristics serve to generate the correct decision in an economical manner. In this sense, expert strategies are immensely adaptive. There is a substantial body of research on medical problem solving [62], and more generally in other domains that illuminate the ways in which solution strategies are instantiated in diverse contexts. This research also suggests a continuum of skill acquisition that could serve as benchmarks for instruction and training. In general, problem-solving studies are more "diagnostic" in specifying potential sources of error as well as characterizing the productive roots of expert performance.

4.2. Conceptual knowledge and decision strategies in medicine

Claim 5. *Conceptual knowledge differs in important respects from procedural knowledge and has a qualitatively distinct and predictable effect on decision practices.*

Decision-making research typically focuses on decision strategies and characterizes acumen in probabilistic judgment. Although decision strategies are equally important in problem-solving research, the explanatory focus is often on differences in content knowledge. Surprisingly, differences in content or conceptual knowledge have received scant attention in the decision literature.

As discussed in the last section, our own research on diagnostic reasoning has been strongly influenced by the problem-solving approach. One of our primary analytic foci is the differential role of basic science knowledge (e.g., physiology and biochemistry) in solving problems of varying complexities and differences between subjects at different levels of expertise (see [62] for a more extended treatment of these issues). This has been a source of controversy in the study of medical cognition [80,81] as well as in medical education and artificial intelligence. As expertise develops, the disease knowledge of a clinician becomes more dependent on clinical experience and clinical problem solving is increasingly guided by the use of exemplars and analogy, becoming less dependent on a functional understanding of the system in question. However, an in-depth conceptual understanding of basic science plays a central role in reasoning about complex problems and is also important in generating explanations and justifications for decisions.

AI researchers were confronted with similar problems in extending the utility of systems beyond their immediate knowledge base. The problem with most first generation systems was that they were inherently brittle in that they exhibited a sudden performance degradation when the problem at hand was near or beyond the limits of their domain knowledge. Many subsequent medical expert systems have attempted to overcome the brittleness problem by explicitly incorporating knowledge of the underlying pathophysiological mechanisms. Biomedical knowledge can serve different functional roles depending on the goals of the system [82]. Most cases of diagnostic reasoning could be construed as a process of classification involving the subsumption of clinical findings under a malfunction hypothesis. However, it is sometimes necessary to identify the structural fault that has led to the aberrant behavior. To engage in this type of causal reasoning, an agent needs knowledge of the space of possible malfunctions and knowledge that relates observations to malfunctions. This necessitates a certain understanding of how behavior, structure, and function interrelate.

Certain expert systems explicitly encoded biomedical knowledge in a multi-level causal network. This approach was exemplified by ABEL, a consultation system for electrolyte and acid–base disorders [83]. ABEL attempted to identify the disease process causing a patient's illness. Knowledge was encoded in a hierarchical semantic network and could explain pathophysiological states in varying degrees of granularity, for example, from clinical levels to specific biochemical processes. ABEL attempted to account for the clinical findings by developing a multi-level explanation of the problem, known as a patient-specific model [83]. The program constructed this explanation by navigating between levels via processes such as aggregation (summarizes the description to the next more aggregate level) and elaboration (elaborates the description to the next more detailed level). The pathophysiological description provided the ability to solve complex clinical situations with multiple etiologies and to organize large amounts of information into a coherent causal explanation [83].

ABEL was but one such example of how "deep knowledge" is needed to confront complex clinical decisions employing causal reasoning and symbolic knowledge. Systems such as MDX-2 [82] or QSIM [84] had an explicit representation of structural components and their relations, the functions of these components (in essence their purpose), and their relationship to behavioral states. The causal and diagnostic knowledge could be generated by "running" or simulating the system and qualitatively deriving behavioral sequences that could identify and explain the malfunction. The knowledge was not precompiled as in ABEL, but could be generated in real time to find fault in a system. This principled knowledge could theoretically be used to generate the widest range of possible diagnostic hypotheses and to explain multi-system conditions that the program had never previously encountered.

The kinds of conceptual knowledge needed to reason productively are an important issue in both medical AI and medical cognition. How to effectively impart this knowledge has also been a subject of much debate in medical education [62]. We now consider studies that examine the relationship between conceptual knowledge and medical decision-making.

Kaufman et al. [85] sketch a cognitive framework for characterizing medical decision-making in patients as well as physicians. The objective of this framework was to describe different kinds of knowledge and reasoning strategies that support healthcare decision practices. It is useful to distinguish among three kinds of knowledge: factual, conceptual, and procedural. Factual knowledge merely reflects knowing a fact or a set of facts (e.g., risk factors for coronary artery disease) without any in-depth understanding. Facts are routinely disseminated through a wide range of sources such as pamphlets and pharmaceutical labels. The acquisition of factual knowledge alone would not necessarily lead to any increase in the understanding or behavioral change. We are particularly suspect of continuing medical or patient education initiatives that promote blind adherence to a course of action without targeting the understanding in any meaningful sense.

The acquisition of conceptual knowledge involves the integration of new information with prior knowledge and necessitates a deeper level of understanding. For example, risk factors may be associated in the physician's mind with physiological and biochemical mechanisms and typical patient presentations. Conceptual understanding can support the explanation and may result in appropriate actions. Procedural knowledge is a kind of knowing related to *how to* perform various activities. It is knowledge that is more instrumentally connected to immediate action. Decision rules, as represented in clinical guidelines, embody a kind of procedural knowledge. In the absence of conceptual knowledge, procedural knowledge has a rather limited range of applicability. Similarly, conceptual knowledge alone may not readily translate into action or appropriate decision choices. This phenomenon, known as inert knowledge, is commonly observed in students who may have an in-depth textbook understanding of disease, but cannot instantiate this knowledge in practical situations.

The integration of conceptual and procedural results in more generative and robust knowledge that is more readily transferable across a range of (superficially dissimilar) clinical situations. However, they are often not tightly integrated and may in fact be in conflict. For example, a physician may demonstrate a certain understanding of specific concepts, but may use decision strategies that are inconsistent with this knowledge. Conversely, a physician may take the appropriate actions or decisions without conceptual understanding. This dissociation may reflect correct performance without articulated knowledge or alternatively, accurate knowledge, followed by inappropriate action. This decoupling of knowledge and action has been documented in several studies of medical decision-making. Poses et al. [55] found that teaching physicians how to improve their estimates of disease probabilities in regard to streptococcal pharyngitis did not affect their treatment decisions. Elstein et al. [86] found that physicians' beliefs and understanding of hormonal replacement therapy was not predictive of the kinds of the decisions that they made when presented with related clinical cases.

Kaufman et al. [85] examined physicians' understanding of concepts and decision-making strategies in problems pertaining to hypercholesterolemia and coronary heart disease. The study was carried out in two phases: (1) a simulated clinical interview in which two clinical problems were presented and (2) a session in which subjects responded to a series of questions. The questions were related to the analysis of risk factors, diagnostic criteria for determining elevated lipid values, and differential diagnoses for lipid disorders. The results indicate that all subjects exhibited gaps in their conceptual understanding. In particular, most physicians demonstrated a lack of knowledge on the primary genetic disorders that contribute to coronary heart disease, as well as deficiencies in understanding the secondary causes of hypercholesterolemia. The majority of subjects tended to overestimate the lipid value intervals for determining patients at high risk. Physicians had no difficulty in diagnosing the first patient problem of familial hypercholesterolemia (a relatively straightforward decision rule of family history coupled with a particular lipoprotein profile), but failed to identify the problem of elevated lipids secondary to hypothyroidism. This necessitates either empirical knowledge of the co-occurrence of hypercholesterolemia and thyroid disease or a mechanistic understanding of the way in which the two are associated.

Procedural and conceptual knowledge are fostered via different learning experiences. For example, continued adherence to a set of clinical guidelines would likely lead to a change in procedural knowledge. After a period of using these guidelines, a physician would be able to internalize the decision alternatives and follow appropriate decision strategies without explicit use of the guidelines. The acquisition of conceptual knowledge necessitates mindful engagement involving reflection and discourse with peers through various forums such as seminars, medical rounds, and continuing medical education. In addition, many computer-based learning environments are developed with the objective of fostering conceptual knowledge. Increasingly, clinical guidelines endeavor to straddle the boundaries between more elaborate explanations intended to foster conceptual knowledge and algorithmic representations (e.g., decision trees) designed to facilitate procedural knowledge. Diverse forms of knowledge have specific effects on medical decision-making and their characterization is necessary for explaining variations in clinical practice. Furthermore, these considerations are important when developing decision support and instructional interventions to enhance the decision-making performance.

4.3. Naturalistic decision-making

Claim 6. *Decision making in "real-world" situations imposes unique demands (e.g. time pressure and stress) on the decision process and these demands are not adequately captured in most laboratory decision studies.*

Naturalistic decision-making (NDM) has emerged as an active area of decision research over the last two decades. This research concerns investigations of cognition in "real-world" work environments that often have a dynamic (e.g., rapidly changing) quality to them [87]. This research was born out of frustration with efforts to apply methods and findings from traditional decision research in these complex settings. What has emerged is something akin to a new paradigm. Decision-making research in naturalistic settings differs substantively from typical decision-making research, which most often focuses on a single decision event, and a fixed set of alternatives in a stable environment [88]. One can argue that traditional and NDM researchers are in fact studying markedly different phenomena [89]. However, both groups are focally concerned with understanding and ameliorating the decision process. In a recent edited volume, Salas and Klein [90] describe NDM as:

> ... the effort to understand and improve decision-making in field settings, particularly by helping people more quickly to develop expertise and apply it to challenges they face. One of the significant features of NDM is that it seeks explicitly to understand how people handle complex tasks and environments. We have found that we cannot study decision-making in isolation from other processes, such as situation awareness, problem solving, planning, uncertainty management, and the development of expertise. (p. 3)

The majority of this research combines conventional protocol analytic methods with innovative methods designed to investigate cognition and behavior in realistic settings [91–93]. The study of decision-making in the work context necessitates an extended cognitive science framework beyond typical characterizations of knowledge structures, processes, and skills to include modulating variables such as stress, time pressure, and fatigue as well as communication patterns in team performance.

Claim 7. *Decision making in realistic settings is often characterized by a serial assessment of a single option rather than the evaluation of a fixed set of alternatives. Systematic weighing of discrete pieces of evidence is the exception rather than the rule.*

Claim 8. *Decisions in high stress situations necessitate immediate response behavior and perceptual cues may play a more prominent role in the decision process.*

Klein and colleagues have undertaken seminal research in the area of dynamic decision-making, working with fire commanders and platoon leaders [94]. The methods employed include field observations and retrospective accounts of actual emergency events. The types of decisions fire commanders were required to make included whether to initiate a search and rescue, whether to initiate an offensive attack on the fire, or whether to use a more precautionary defensive strategy. Commanders acted on the basis of prior experience, immediate feedback, and careful monitoring and assessment of the situation. They used a process of serial evaluation of options rather than systematically selecting between alternatives or weighing probabilities (either subjectively or explicitly). The results indicated that expert commanders relied more extensively on strategies of situation recognition, using minimal deliberation, whereas less experienced or novice commanders tended to employ a more deliberative decision-making approach. This kind of recognition-primed decision-making appears to be characteristic of dynamic decision-making environments [95]. Expert decision makers often recognize a situation as being similar to ones they have previously encountered and negotiated successfully. This provides a basis for effective solution strategies. Skilled decision makers are also said to engage in a process of situation assessment. This is characterized by a concerted effort to understand or "size up" the situation rather than to generate decision options. This is somewhat similar to the finding that expert problem solvers devote considerably more time to representing the problem, whereas novices are much more likely to jump right in and attempt to rapidly generate hypotheses [76] or implement a solution [96]. In the hands of a skilled problem solver, the solution sometimes appears to emerge from the representation. Similarly, a forward-directed reasoning strategy is contingent on a coherent problem representation.

NDM researchers[8] have studied a wide range of problems in different domains such as air traffic control, nuclear power plant management, software design,

[8] NDM research is not a monolithic entity. Rather NDM researchers embrace diverging theoretical and methodological approaches. Grouping them under one rubric runs the same risk as categorizing decision-making researchers as adherents to a traditional or classical approach.

military command and control, financial planning, and forensic science. In this section, our focus is predominantly on NDM research conducted in healthcare settings with particular attention to research conducted in our own laboratory.

Leprohon and Patel [60] studied the decision-making strategies used by nurses in emergency telephone triage settings. In this context, nurses are required to respond to public emergency calls for medical help (exemplified by 911 telephone service). The study analyzed transcripts of nurse-patient caller telephone conversations of different levels of urgency and complexity and interviewed nurses immediately following their conversations. In decision-making situations such as emergency telephone triage, there is a chronic sense of time urgency—decisions often have to be made in seconds. This may involve the immediate mobilization and allocation of resources. Decisions are always made on the basis of partial and sometimes unreliable information.

The results were consistent with three patterns of decision-making that reflect the perceived urgency of the situation. The first pattern corresponds to immediate response behavior as reflected in situations of high urgency. In these circumstances, decisions are made with great rapidity. Actions are typically triggered by symptoms or the unknown urgency level in a forward-directed manner. The nurses in this study responded with perfect accuracy (i.e., allocating the proper resources to meet the demands) in these situations. The second pattern involves limited problem solving and typically corresponds to a situation of moderate urgency and to cases that are of some complexity. The behavior is characterized by information seeking and clarification exchanges over a more extended period of time. These circumstances resulted in the highest percentage of decision errors (mostly false positives). The third pattern involves deliberate problem solving and planning and typically corresponds to low urgency situations. These situations involved evaluating the whole situation and exploring options and alternative solutions, such as identifying the basic needs of a patient and referring the patient to an appropriate clinic. The nurses made fewer errors than in situations of moderate urgency and more errors than in situations requiring immediate response behavior. They could accurately perceive a situation as not being of high urgency. Decision-making accuracy was significantly higher in nurses with 10 years or more of experience than nurses with less experience, which is consistent with the acquisition of expertise in other domains.

Most decisions were based on symptoms rather than on diagnostic hypotheses, especially in urgent situations. These decisions rely on prior instances that facilitate rapid schema access, based on minimal information and enable them to represent the situation to gather information and make decisions. Nurses learn to recognize critical symptoms that evoke decision heuristics. This finding is consistent with the research by Benner and Tanner [97] who found that nurses respond on the basis of prior experiences in memory and do not decompose decisions into sets of alternatives or attempt to understand the underlying pathophysiology of a patient problem. Nurses' training, which focuses on observational skills and detection of abnormal and urgent symptoms, would contribute to the acquisition of this type of decision-making process. Benner also suggests that experience-based knowledge forms the basis of much of nurses' intuitive clinical judgments.

Crandall and Calderwood [98] studied nurses' decision-making about patients with sepsis in a neonatal intensive care unit. They employed an interview methodology known as the critical decision method, which involves asking individuals about particularly challenging incidents and probing for cues that resulted in particular decisions. The findings indicated that experienced nurses rely heavily on perceptually based indicators and findings not documented in the medical literature. The nurses were very sensitive to subtle changes in an infant's condition, were able to detect trends early on in the clinical course, and predicted potentially adverse outcomes (a worsening septic shock). The researchers elicited much of this information through probes, since nurses had difficulty in verbally explaining the perceptual cues.

Claim 9. *Team decision-making is characterized by emergent properties that cannot be captured by merely studying individual decision makers*

We have been engaged for the last eight years in the study of decision-making in critical care settings (emergency departments and intensive care settings). Our objectives are to understand: (1) how decisions are jointly negotiated[9] and updated by participants differing substantially in their areas of expertise (e.g., pharmacology, respiratory medicine); (2) the complex communication process that is routine in these settings; (3) the role of technology in mediating decisions, (4) the sources of error in the decision-making process, and (5) how pedagogy and the apprenticeship process are integrated into the work settings.

Patel et al. [61] studied decision-making in a medical intensive care unit (ICU). The principal sources of data included audio tape recording of medical morning rounds, complete patient charts and records, and interviews with the participants. The goals of the ICU are: (a) first to stabilize the patient and then identify and treat the underlying problem and (b) to coordinate collection, analysis, and management of data from the various

[9] Jointly negotiated decisions do not necessarily suggest a democratic decision process or that each participant has an equal voice.

sources, which involves coordination and distribution of workloads to various participants, namely residents, nurses, laboratory technicians, pharmacists, and nutritionists. The team's decision-making involves: (a) management of multiple streams of information and (b) communication and coordination among individuals and from different data sources. Team leaders hierarchically ultimately control most decisions and actions, but expertise is distributed among individuals and responsibility is allocated among the team to maximize efficiency.

The medical team's goals continuously shift as the patient's condition changes and new problems or complications arise. These complications often result in rapidly shifting goals and changing priorities. In the course of treatment, physicians constantly encounter new data that lead them to make changes in the patient-management regimen. The data sources include laboratory tests, nurse reports, expert consultations, output from various patient monitoring devices, and new findings revealed in the examination of a patient. In realistic settings, cognition can appropriately be construed as distributed [99]. The idea is that other individuals and external artifacts (such as computers and instruments) do not merely add to the cognitive process, but transform it in significant ways [100]. The combined products of a cognitively distributed system (e.g., multiple team members) cannot be accounted for by operation of its isolated components. However, each of the entities or individuals can still be seen as having personal attributes such as knowledge and skills, some of which are an integral part of the "distributed partnership" and others which are not [99]. This issue is discussed further in the context of technology-mediated decision-making in the next section.

Intensive care decision-making is characterized by a rapid serial evaluation of options, leading to immediate action. In this real-time decision-making, the reasoning is schema-driven in a forward direction towards action with minimal inference or justification. The results of the action (as measured by the patient's response) feed back into the decision-action cycle and the proper course of further action ensues. When the circumstance is ambiguous or the patient did not respond in a manner consistent with the original hypothesis, then the original decision comes under scrutiny. This can result in a brainstorming session where the team retrospectively evaluates and reconsiders the decisions that had been made and considers several possible alternative future courses of action. We have observed several such distinct patterns of decision-making. The goals of these reflective sessions are: (a) to critically evaluate decisions that are made, (b) to rationalize and debate decisions and actions that are taken, and (c) to discuss future plans of action. The multiple kinds of reasoning used to evaluate alternatives include probabilistic reasoning, diagnostic reasoning, and biomedical causal reasoning. An investigation of the cognitive processes involved in these reflective sessions reveals a number of important mechanisms related to coordination of theory and evidence [101].

This kind of retrospective evaluation is exemplified in a weekly session where all attending physicians and staff meet to discuss various patient problems. The discussion focused on the treatment of an ICU patient who had suffered a cardiac arrest. He was treated with streptokinase, a potent blood-thinning agent, on his arrival at the emergency room. The participants in the evaluation session included cardiologists, respiratory therapists, residents, and students. The positive evidence in favor of the use of streptokinase is that it is the usual treatment strategy for patients showing signs of myocardial infarction (abnormal ECG patterns) and it can reduce morbidity and mortality. The ICU patient was stabilized when he was treated with streptokinase. However, the patient suffered subsequent bleeding, which is a common side affect of this medication. The critical question was whether the ECG provided conclusive evidence of myocardial infarction, and, since only a small percentage of the people benefit from this treatment, whether the decision for this particular patient was valid. In this particular session, two respiratory therapists argued that the patient had received the appropriate therapy and two cardiologists argued to the contrary. They collectively constructed the sequence of events, debated over the interpretation of specific evidence such as the results of the electrocardiogram, discussed a priori probabilities, and its interpretation in this context.

These sessions serve a valuable pedagogical role in that they help articulate assumptions that would not normally be discussed during clinical rounds. In actual practice, there is little time available for engaging in the deliberative weighing of multiple decision alternatives or extended causal reasoning. Nevertheless, the underlying causal models are sometimes critical to supporting real-time decision-making. These types of learning environments help foster the development of such a knowledge. Such learning is often crystallized (i.e., made explicit to the learner) after the fact in grand rounds and other less formal discussion formats.

More recently, we have extended our research to a range of critical care environments including surgical intensive care, pediatric, and psychiatry emergency departments [102]. These are all distinct clinical settings that have unique organizational structures and deal with patient problems involving very different forms of decision-making. An interesting point of difference is that medical intensive care units have a greater diffusion of responsibility and heterarchical decision processes, whereas surgical ICUs appear to be characterized by a stronger centralized chain of decision authority and hierarchical decision processes. The workflow process also critically shapes the decision process. For example, the processing of a patient in an emergency department follows a relatively linear and orderly process from the reception area into nursing triage and so forth. On the other hand, such patterns are decidedly less linear and predictable in medical ICU settings. Perrow [103] introduces a useful distinction between complex and linear systems. Complex systems are characterized by a high degree of specialization and interdependency among agents or components (including technologies) and multiple feedback loops. For example, patient management in an ICU setting is characterized by continuous cycles of administering aggressive therapies and monitoring and countering their side effects [61]. The process of patient care in emergency departments is somewhat more modular and less interdependent than in an ICU, although it is important to point out that the difference is a matter of degree rather than kind. For example, the interdependency in an emergency department is evidenced by the triage process, which provides a direction and commits a set of resources for the care of a patient. Each stage of the triage critically shapes the ensuing decisions and actions that follow in subsequent stages of the patient care process. However, the ICU appears to be characterized by a more complexly entangled set of dependencies thereby creating more possibilities for errors. These distinctions provide a basis for characterizing differences in workflow, communication patterns, technology use, and opportunities for different kinds of learning. In our view, it is vitally important to understand better how these factors differentially shape the decision process.

Supporting decision-making in clinical settings necessitates an understanding of both workflow and communication patterns. Several studies have documented that communication between individuals is both the primary source for addressing information needs (e.g., [104]) and a significant source of medical error. Coeira [105] makes a compelling argument that the computational view of decision support as "acquiring and presenting data" is too narrowly conceived. He espouses a view in which conversations are best characterized by "the fluid and interactive notions of asking and telling, inquiring and explaining" (p 278). He argues that the communication space is the largest part of the health system's information space, constituting the bulk of information transactions and clinicians' time. There are two broad implications to this view. The first is that technology that directly supports communication among clinicians should greatly improve how organizations acquire, present, and use information. The second view suggests that developing a richer understanding of communication tasks should enable us to employ communication and information technologies more productively to address information needs and decision processes. Coeira's perspective is generally consonant with the viewpoint of NDM. His work is also compatible with the view that all technologies differentially mediate decision processes, which is the subject of the next section.

In general, NDM research has provided a fresh perspective for understanding decision-making as it occurs in the real-world environment. The approach offers unique theoretical and methodological insights. However, it is not without its detractors (see Yates [89] for a balanced discussion). The approach is largely a descriptive one and does not offer a clear gold standard for evaluating the quality of decisions. In addition, it is difficult to draw conclusive generalizations from any one study given the fact that it is conducted in relatively few settings (often only one). Moreover, like traditional decision research, NDM does not have a sterling track record in developing effective models for training and decision support (although this is an active area of research). Part of the problem is that the descriptions are couched in high-level abstractions (e.g., archical decision processes) and the precise implications are difficult to discern or adopt. Paradoxically, there is a need for both fine-grained analysis of decision and communication processes and quantitative studies that compare settings on a few measures. However, NDM has considerably broadened the landscape for decision research and has focused our attention on the immensely adaptive nature of skilled decision makers.

4.4. Technology-mediated decision-making

Claim 10. *Technologies mediate the decision-making process in distinct and often counterintuitive ways that can produce unintended consequences.*

Claim 11. *Decision technology does not merely facilitate or augment decision-making rather it reorganizes decision-making practices.*

All technologies mediate human performance. What do we mean by mediate? Technologies, whether they be computer-based or in some other form, transform individuals' and groups' cognition and the ways that they work. They do not merely augment, enhance or expedite performance, although a given technology may do all of these things. The difference is not one of quantitative but rather of qualitative change. The mediating role of technology has long been recognized in human factors. Recent reports on errors in medicine have clearly delineated that the interface between humans and technology is a primary source of error [4]. In some respects, this is a non-contentious or even an obvious point. However, it is the one that has received inadequate attention in the decision-making community. In this section, we endeavor to clarify the idea of mediating and illustrate it in contexts of both *high* and *low* (e.g., paper-based guidelines) technologies. First, let us briefly consider a strong form of the mediation argument put forth by proponents of the situated cognition and/or sociotechnical perspective.[10]

The distributed view of cognition represents a shift in the study of cognition from being the sole property of the individual to being stretched across groups, material artifacts, and cultures [19]. The situated and sociotechnical schools of thought acknowledge that much of everyday cognition is embedded in social practices and interwoven with the use of artifacts [106,107]. This has theoretical, methodological, and practical consequences for the design and implementation of technologies. Cole and Engestrom [108] argue that the natural unit of analysis for the study of human behavior is an activity system, comprising relations among individuals and their proximal, "culturally organized environments." A system consisting of individuals, groups of individuals, and technologies can be construed as a single indivisible unit of analysis. Berg [109] is a leading proponent of the sociotechnical point view within the world of medical informatics. He argues that:

> Work practices are conceptualized as networks of people, tools, organizational routines, documents and so forth. An emergency ward, outpatient clinic or inpatient department is seen as an interrelated assembly of humans and things whose functioning is primarily geared to the delivery of patient care.... [A few paragraphs later] The elements that constitute these networks should then not be seen as discrete, well-circumscribed entities with pre-fixed characteristics. (p 89)

In his view, the study of information systems must eschew an approach that fractionates individual and collective, human and machine, as well as the social and technical dimensions of information technology. Berg also argues for a participant observation methodology that will enable deep empirical insight into the work practices in which any technology is used. He also argues against the use of rigid formal models, standards, or algorithmic approaches to reducing variability in practice. Although Berg is not in principle opposed to decision-support technologies, he views them as having a transformative and unpredictable effect on medical practice [109]. Bowker and Starr [110] draw on similar theoretical notions in their penetrating analysis of the social construction of classification systems and standards and their unintended consequences.

We find this perspective to be particularly compelling and have learned much from this approach, particularly in our research of decision-making in naturalistic settings [61] and computer-mediated collaborative design [111]. However, our perspective differs in important respects from a sociotechnical or situated point of view in that the role of the individual figures prominently in our analysis [112]. Additionally, we advocate a methodological pluralism that focuses on different levels of analysis [113]. For example, at the most basic level, our analyses focus on the technology itself and study its design, affordances, and the kinds of cognitive challenges it is likely to present to a population of users [113]. Towards the other end of the continuum, we study the process of distributed decision-making in various clinical settings. The task-analytic information-processing approach offers a robust set of methodological and theoretical tools to understand cognition, whereas the situated approach helps us to understand how social entities jointly make (or distribute) decisions and cognitive resources [114]. The situated/distributed approach also provides a basis for understanding how communication is grounded through the use of various mediating communication technologies (e.g., email) and across geographic distances, how groups jointly learn to attain a satisfactory level of team performance, and the ways in which organizational entities are constituted to produce (and sometimes obstruct) work.

The mediating role of technology can be evaluated at several levels of analysis. For example, electronic medical records alter the practice of individual clinicians in significant ways as discussed below. Changes to an information system substantially impact organizational and institutional practices from research to billing to quality assurance. Even the introduction of patient-centered medical records early in the twentieth century necessitated changes in hospital architecture and considerably affected work practices in clinical settings [109]. Salomon et al. [115] introduce a useful distinction in considering the mediating role of technology on individual performance, the *effects with* technology and the *effects of* technology. The former is concerned with the changes in performance displayed by users while being equipped with the technology. For example, when using an effective medical information system, physicians should be able to gather information more systematically and efficiently. In this capacity, medical information technologies may alleviate some of the cognitive load associated with a given task and permit them to focus on higher-order thinking skills, such as hypothesis generation and evaluation. The *effects of* technology refer to enduring changes in general cognitive capacities (knowledge and skills) as a consequence of interaction with a technology. For example, frequent use of information technologies may result in lasting changes in medical decision-making practices, even in the absence of the system.

The mediating role of technology on clinical decisions has been studied in a wide range of situations and

[10] It is once again necessary to point out that lumping schools of thought together under a single rubric inevitably simplify distinct perspectives and points of view. Situated and sociotechnical categories reflect a wide range of methodological and theoretical approaches to understanding technology, drawing on predominantly anthropological and sociological schools of thought.

technologies from laparoscopy [116] to airway management [117]. Technologies often effectively mediate clinical decisions, resulting in improved performance. However, they sometimes result in predictable patterns of error [118] and at other times have surprising effects whose consequences are difficult to gauge. We have conducted several studies evaluating the effects of electronic medical records (EMRs) on information gathering, data representation, and decision practices. EMRs differ substantially in terms of their functionality, use of controlled medical vocabulary, and graphical user interface. All of these have differential effects on decision practices.

The particular system used in one set of studies was a pen-based EMR system [119]. Using the pen or computer keyboard, physicians could directly enter information into the EMR, such as the patient's chief complaint, past history, history of present illness, laboratory tests, and differential diagnoses. The system incorporated an extended version of the ICD-9 vocabulary standard. The EMR allowed the physician to record information about the patient's differential diagnosis, the ordering of tests, and the prescription of medication. The system also provided supporting reference information in the form of an integrated electronic version of the Merck Manual, drug monographs for medications, and information on laboratory tests. The graphical interface provided a highly structured set of resources for representing a clinical problem. To enter the medical findings, the physician determined the context of the visit. For example, if the patient presented with a specific complaint such as abdominal pain, the physician would select a clinical note template (CNT) for abdominal pain, which displayed a selection of the medical findings and observations on the computer screen.

We studied the use of this EMR in both laboratory-based research [119] and in actual clinical settings [120]. We observed two global patterns of EMR usage in the interactive condition: one in which the subject pursues information from the patient predicated on a hypothesis they have formulated and a second involving the use of the EMR display to provide the subject with guidance for requesting information. All experienced users of this system appeared to use both strategies. There appears to be a point in the process of skill acquisition, whereby the second screen-driven strategy is incorporated in the user's repertoire.

In general, a screen-driven strategy can enhance the performance by alleviating the cognitive load imposed by information gathering goals and allowing the physician to allocate more cognitive resources for discriminating among hypotheses and making complex decisions. On the other hand, this strategy can induce a certain sense of complacency and perhaps imbue the device with a certain intelligence that it does not really possess. We observed both effective as well as counterproductive uses of this screen-driven strategy. A more experienced user deliberately used the strategy and was able to exploit the affordances offered by the system to structure a (simulated) doctor-patient encounter, whereas a novice user was demonstrably less successful in her pursuit. The subject used the structured list of findings on the screen to prompt her to ask questions. In employing this screen-driven strategy, she elicited almost all of the relevant findings in a simulated patient encounter. However, she also elicited numerous irrelevant findings and pursued incorrect hypotheses. In this particular case, the strategy seemed to induce a certain cognitive complacency and the subject had difficulty in imposing her own set of working hypotheses to guide the information-gathering and diagnostic-reasoning processes.

The differential use of strategies is evidence of the mediating *effects with* technology. We extended this line of research to study the cognitive consequences of using the same EMR system in a diabetes clinic [120]. The research combined qualitative and quantitative analyses focusing on the levels of physician's interactions with the system as well as doctor-patient interaction. The study considered the following questions ([120], p 571): (1) how do physicians manage information flow when using an EMR system? (2) What are the differences in the way physicians organize and represent this information using paper-based and EMR systems? And (3) are there long-term, enduring effects of the use of EMR systems on knowledge representations and clinical reasoning. We have reported several interrelated studies with the first focusing on an in-depth characterization of changes in knowledge organization in a single subject as a function of using the system. The study first compared the contents and structure of ten patient records, matched for variables such as age and problem type, produced by the physician using the EMR system as well as paper-based patient records. After having used the system for six months, the physician was asked to conduct his next five patient interviews using only hand-written paper records.

The results indicated that the EMRs contained more information relevant to the diagnostic hypotheses. In addition, the structure and content of information were found to correspond to the structured representation of the particular medium. For example, EMRs were found to contain more information about the patient's past medical history, reflecting the query structure of the interface. The paper-based records appeared to preserve the integrity of the time course of the evolution of the patient problem, whereas this was notably absent from the EMR. Perhaps, the most striking finding is that, after having used the system for six months, the structure and content of the physician's paper-based records bear a closer resemblance to the organization of information in the EMR than did the paper-based records produced by the physician, prior to the exposure to the system. This finding is consistent with the enduring *effects of* technology, even in the absence of the particular system.

We also conducted a series of related studies with physicians in the same diabetes clinic [120]. The results of one replicated and extended the results of the single subject study (reported above) regarding the differential effects of EMRs and paper-based records on represented (recorded) patient information. For example, physicians entered significantly more information about the patients' chief complaint using the EMR. Alternatively, physicians represented significantly more information about the history of present illness and review of systems using paper-based records. It is reasonable to assert that such differences are likely to have an effect on clinical decision-making. The authors also video-recorded and analyzed 20 doctor-patient computer interactions by two physicians varying in their level of expertise. One of the physicians was an intermediate-lever user of the EMR and the other was an expert user. The analysis of the physician-patient interactions revealed that the less-expert subject was more strongly influenced by the structure and content of the interface. In particular, he was guided by the order of information on the screen when asking the patient questions and recording the responses. This screen-driven strategy is similar to what we documented in a previous study [119]. Although the expert user similarly used the EMR system to structure his questions, he was much less bound to the order and sequence of presented information on the EMR screen. This body of research documented both *effects with* and *effects of* technology in the context of EMR use. These include effects on knowledge-organization and information-gathering strategies. The authors conclude that given these potentially enduring effects, the use of a particular EMR will almost certainly have a direct effect on medical decision making.

The mediating role of technology can also be seen in the use of clinical practice guidelines, where different effects can be observed on different types of users. Two of the major aims in developing clinical practice guidelines are to standardize and improve the quality of care. However, their implementation in healthcare environments has produced less than desired results [121,122]. For clinical practice guidelines to be widely adopted, they need to become part of the normal clinical environment with which the physician interacts. Guidelines must mediate decisions in a manner consistent with the temporal flow of clinical reasoning [123]. To ensure optimal usability, guidelines need to be tuned to specific types of user. Studies of guideline utilization [114], in which expert physicians and non-expert physicians used algorithmic and text-based guidelines, show that whereas clinical practice guidelines are used as reminders by both expert as well as non-expert physicians, they also serve other functions depending on the expertise. Guidelines serve to constrain the problem-solving process of experts (by focusing the physician's attention on important aspects) but serve as educational devices for the non-experts (by suggesting disease alternatives that were not originally thought about). The different ways in which guidelines mediate decisions among different populations of users is an area in need of further research.

5. Conclusions

The traditional or classical approach has served as a wellspring for both theoretical and applied decision researche for more than half a century. It has also served to advance the practice of decision-making in healthcare settings. By most accounts, it is an immensely successful research enterprise. However, there are several significant limitations to the traditional decision research program, some of which have been enumerated in the paper. To recapitulate, normative models have yielded disappointing returns as reliable guides to decision-making. Also, empirical work based on the normative approach has proved to be somewhat simplistic and limited as a model of actual, real-world decision-making, notwithstanding its accomplishments. We argue for a decision science that broadens the boundary of traditional decision-making research. In particular, there is a need for an expanded empirical scope employing a greater range of methodologies and a greater emphasis on ecological validity (understanding the dynamics of real-world settings).

This broadening can be understood along several dimensions. First, in our view, the contrast between decision-making and problem-solving research is rather illuminating. Problem-solving research emphasizes: (1) understanding skilled performance as realized by experts, (2) understanding the decision-making process, and (3) recognizing conceptual knowledge as both a resource to aid decisions and a contributor to patterns of misunderstanding, leading to suboptimal decisions. The view is that expert decision makers (or problem solvers) have immensely adaptive, albeit imperfect strategies for overcoming information-processing limitations. Heuristics and biases are rooted in productive decision-making.

Second, the naturalistic decision-making approach focuses on real-world settings and places a premium on the descriptive adequacy of models. This necessitates a commitment to in-depth qualitative methodologies.[11]

[11] This does not in any way preclude quantitative analyses or models. In many contexts, they are complementary methods and provide a necessary measure of convergence.

The characterization of performance in these settings is often at variance with the classical rational, deliberative, and calculating decision maker. Stress, time pressure, and risk (among other factors) necessitate the development of adaptive strategies that correspond to the constraints of a particular situation. In addition, these strategies may be the product of individuals or teams. The social and collaborative dimensions of decision-making warrant a closer scrutiny if decision-support technology is to infiltrate the ebb and flow of daily work.

Third, the differential role of technology cannot be ignored. Technologies are mediators of performance and serve to reorganize practice rather than merely to produce a quantitative gain in performance. This changes the way we think about decision-support technologies. These need to be understood in the context of practice, where there is a need for a deeper understanding of a) performance in actual settings; b) effects of technology propagating through the different layers of an organization; and c) the adaptability of health professionals (and consumers of healthcare services) to an increasingly technologically mediated world.

In this paper, we endeavored to characterize the strengths and weakness of traditional decision-making research and suggested some promising new directions. However, we did not put forth a grand synthesis in which the two approaches are seamlessly melded into a coherent whole. At minimum, this synthesis would need to account for the 11 claims articulated in this paper. There are numerous remaining methodological and epistemological challenges in erecting a comprehensive decision-making framework. In our view, we know a great deal more about decision-making and decision makers than we have realized. A reconstituted basic science framework could make the rather impressive accomplishments of decision research more transparent. We remain optimistic that we can more fully exploit that knowledge in designing and implementing technologies that can facilitate decision processes in real-world clinical settings.

Acknowledgments

We owe our thanks to many researchers and graduate students who contributed to this paper by providing valuable discussions. We especially thank Ted Shortliffe and two anonymous reviewers for their critical comments on the earlier drafts of the manuscript. Preparation of the manuscript was supported in part by the National Library of Medicine under Grant LM06594, with additional support from the Department of the Army and the Agency for Healthcare Research and Quality, and by Grant MRC-MA 13439 from the Canadian Institute for Health Research awarded to Dr. Patel.

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