Decision Architectures

2

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Introduction

At the core of many of the quality improvement initiatives spearheaded by the U.S. Institute of Medicine (IOM) was an assumption that medical communication and decision-making must be improved in order to achieve true population benefits from evidence-based medicine. Medicine is an information-intensive enterprise, argued the authors of the IOM report "*Crossing the Quality Chasm: A New Health System for the 21st Century*" (Institute of Medicine 2001). The only sustainable way to improve patient outcomes is to reengineer the *systemic architectures of medicine* to ensure that the right information is delivered to the right people in the right way to improve the quality of care (Reid et al. 2005; Hesse and Shneiderman 2007). This was the rationale underlying passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, which sought to improve patient care by delivering better cognitive and decision support to health care providers, patients, and family caregivers. It was also the rationale underlying many of the provisions of the Affordable Care Act of 2010, which sought to reengineer incentives within health care to emphasize prevention, patient engagement, continuity of care, and cost effectiveness (Hesse 2010; Stead and Lin 2009). The U.S. House Appropriations Committee added further reinforcement when it highlighted "health decision-making" as an important focus for ongoing research and development within the priorities of the National Institutes of Health (NIH) in 2011 (The Cancer Letter 2011; President's Council of Advisors on Science and Technology 2010).

Strains Within the System

The need for continued work in the area of supported decision-making sounds well and good, but what does it really mean to say that health systems researchers need to reengineer the systemic architectures of medicine? Isn't this what eight (+) years of advanced medical education in the classroom and residency programs, plus a plethora of up-to-date science articles in advanced medical journals, are supposed to accomplish? Aren't physicians and patients used to making effective decisions unassisted by decision aids or information technologies?

To be sure, training is an important and necessary part of medical judgment; but unaided decision-making is rapidly becoming insufficient in a world of information-intensive medicine. As hard as it may be to believe, the first Randomized Controlled Trial (RCT) in medicine was only

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published in 1952 (Daniels and Hill 1952). Staying abreast of the medical literature in 1952 when scientific publications from randomized controlled trials were few and far between may have been a reasonable task. By 2003, though, the U.S. National Library of Medicine estimated that it had been adding almost 10,000 new articles per week within its own online archives—a number that represented only about 40 % of all medical articles published worldwide in biomedical and clinical journals. To stay abreast of the exploding research base just within one specialty would require practitioners to read upwards of 20 articles per day, 365 days a year (Shaneyfelt 2001). That is an impossible task.

To complicate matters further, medical decision-making is by its nature becoming much more data intensive (Topol 2012). By one account, the average number of facts a physician would need to bear in mind when making a decision about a patient's treatment in 1990 was around five (Smith et al. 2012). These were decisions based on an evaluation of the clinical phenotype only; that is, decisions in which the medical practitioner's task would primarily be to evaluate the signs and symptoms accompanying a chief complaint and then to apply a type of one-size-fits-all formulary to match the hypothesized diagnosis with a population-based guess on treatment. Medicine is becoming much more predictive and personalized than that today (Culliton 2006; Collins 2010). Genomic indicators, functional expressions of DNA transcriptions, and molecularly precise assessments of treatment efficacy will create a reality in which the treating physician must take into account 1000 or more facts over the course of a patient's treatment. Cognitive research suggests that the number of facts a human information processor can manage at any given time hovers at around 7 (±2) (Miller 1956). Under the projections of precision medicine, it is difficult to consider a future that does not explicitly include the design of efficient decision architectures to improve the ways in which clinical teams and their patients make ongoing judgments related to care (Institute of Medicine and McClellan 2008).

Failing to Support Patient Engagement in Decision-Making

Not only have strains in the system made it difficult to support physicians' decision needs, but it may also be failing to support patients' informed participation in their own care. In other sectors of the economy, consumers have been learning to interact with complex information systems in ways that are responsive, user-centered, and empowering. Whether relying on a seamless network of Automated Teller Machines and online bill paying to access their own money in any currency around the world, benefiting from the unparalleled safety records of an integrated air traffic control system, or simply reaching their own personal destinations with the help of a user-friendly Global Positioning System (i.e., GPS), consumers have come to depend on state-of-the-art information architectures to navigate the choices of their daily lives (Obama 2012). This has not necessarily been the case in health care.

Consider an all too familiar scenario. A patient waits until a medical problem has progressed to the point of extreme discomfort or reduced functioning before visiting a physician. If this is the patient's first visit to a physician's office, the receptionist may ask her to fill out a form listing all of the medications she may be currently taking; all of the medications she had previously taken; any remembered side effects or deleterious interactions from previous treatments; any persistent complaints or recollections of diagnosed conditions; blood type or other relevant biologic assessments; and a cursory explanation for the purpose of her visit. More often than not, these patients *will not* have brought their own records with them, and they will likely

find it impossible to remember the technical names of pharmaceuticals they might have taken previous to the visit. They may even find it difficult to remember the names and prescribed dosages of medications they are taking currently.

After completing the intake forms, the patient is then escorted to an examination area where a few cursory measures of weight, height, blood pressure, and temperature are added to the patient's newly initiated file. The results are recorded, and the patient is instructed to disrobe and wait until the doctor is ready. After a few seemingly interminable moments the physician comes into the room, quickly peruses the chart and briefly asks a few clarifying questions, performs a focused physical examination, and then writes a prescription. To the patient, the prescription appears to be written in code, with abbreviated Latin terms for mode and frequency of administration (e.g., "p.o." for per os, or by mouth; "q 3 h" for quaque 3 hora, or "every three hours"). If there is accompanying literature, the formatted small print and technical jargon will look more like a legal disclaimer than a set of coherent, easy-to-follow instructions (McClellan 2008).

In the event the physician is not able to reach a firm diagnosis within the 15 min customarily allotted for a clinical encounter, the patient may be given instructions for visiting a laboratory or specialist. Responsibility for the handoff is frequently put on the shoulders of the patient with instructions to make the follow-up appointment, to request that the appropriate records be transferred, and to ensure that insurance will cover the extra expense. The patient will then proceed from one appointment to the next, repeating the chief complaint and brief history along the way. Office staff will take new notes and record them into an expanding chart, though the patient may not have any idea what information or how much information has been transferred between offices. The patient's files grow—with more insurance forms and more technically framed descriptions of services—while at the same time the patient's sense of decisional control grows more tenuous (Taplin and Rodgers 2010).

The Consequences

The consequences of these systemic strains on the decision systems in medicine and health have become severe, especially when considered at the population level. Up until 1999, hospital staff intuitively knew that avoidable errors were occurring with some regularity within their system. In 1999, the Institute of Medicine put a population level count on the consequences of those errors by estimating that some 48,000–98,000 deaths occurred annually due to some type of avoidable medical error (Kohn et al. 2000). That figure exceeded the number of individuals dying from AIDS, breast cancer, or automobile accidents at the time it was reported. Actuarial data from 2008 suggested that the annual cost of measurable medical errors resulting in direct harm to patients as assessed through medical claims was $17.1 billion (Van Den Bos et al. 2011). The practice of medicine used to be "simple, largely ineffective, and relatively safe," argued Sir Cyril Chantler in an oft-quoted Lancet article. With advances in modern medical technology, medicine is rapidly becoming much more effective, but it is also becoming much more complex and extraordinarily dangerous (Chantler 1999).

Contrast these numbers with the number of avoidable deaths from an equally technology-dependent, complex system: aviation. On April 27, 2012, the U.S. National Transportation Safety Board (NTSB) reported that there were *zero fatalities* involving U.S. air carriers or commuter operations in 2011. According to the press release, 2011 was the second straight year in which no fatalities were observed from air travel among U.S. carriers (National Transportation Safety Board 2012).

This remarkable statistic was reported in spite of the fact that there was a small increase in the number of observed accidents or near misses in the industry overall in 2011. Even when factoring in deaths from previous years, the number of fatalities is astonishingly low in the airline industry. The NSTB had reported that the overall number of fatalities over the previous decade was about three deaths per 10 billion passenger miles traveled per year (Insurance Information Institute 2012). That makes a stark contrast to the 48,000–98,000 deaths from medical error estimated to occur annually during the same period (Kohn et al. 2000).

Why is there such a contrast between these two sectors of the economy? This is the question posed by Donald Berwick, Director of the Centers of Medicare and Medicaid from 2009 to 2011. He has concluded that there are significant differences in the contextual fabrics of medicine and aviation that account for these vast differences. In medicine, he observed, a perverse system of "fee-for-service" incentives has created a decentralized medical environment in which adherence to evidence-based approaches for treatment is spotty; the use of risky, and often unnecessary, treatments is prevalent; and an assessment of end-to-end quality control is infeasible (Berwick 2002; Berwick et al. 2008). National health care reform efforts are working to change those incentives while establishing the data infrastructure needed to track patients across health systems (President's Council of Advisors on Science and Technology 2010).

Another reason why the aviation system may be superior in its control of error is the investment it has made in understanding the psychology of human technology interaction, a field known historically as "human factors" research. There have been two antiquated cultures in modern times, reasoned human factors scientist Kim Vincente: one based on a mechanistic, engineering view of the world and one based on a very humanistic, social view of the world. The first view assumes that most problems can be solved through new and better technology—that the answer to bad technology is more technology; while the second assumes that the locus of all problems lies within people—that the way to fix problems is through more education, more rewards, or a culture of "blame and shame." Neither of these worldviews is sufficient on its own to guarantee safety and efficiency in a technology-dependent industry such as aviation or health care. Separated, they are leading to a hidden epidemic of error and chaos (Vicente 2003).

What human factors researchers discovered when performing root-cause analyses of accidents and near misses in aviation (i.e., using specialized analytic techniques to identify the originating cause, rather than symptom, of a critical error) was that the technological and human subsystems are *inextricably linked* and must be studied *together* to improve performance within systems. This combined, or transdisciplinary (Stokols et al. 2008), view is based on the observations: (a) that technical systems have social consequences; (b) that social systems have technical consequences; (c) that systems engineers do not create technologies, they create sociotechnical systems; and (d) that progress within these systems must be gained by understanding how people and technologies interact. In medicine this view is referred to as a sociotechnical perspective on health system redesign (Coiera 2004). Within the National Academy of Sciences, this focus has been referred to as "*Human System Integration*" (Committee on Human-System Design, N.R.C. 2007).

Nudging Best Practice: A Behavioral Economics Approach

Behavioral economists Thaler and Sunstein popularized the notion of improving the systemic architectures upon which individuals make day-to-day decisions in their book "*Nudge: Improving Decisions about Wealth, Health, and Happiness.*" What these two authors were able to do was bring together decades of research in human factors, cognitive psychology, and social psychology to dispel the Cartesian notion popular in classical economics that human judgment

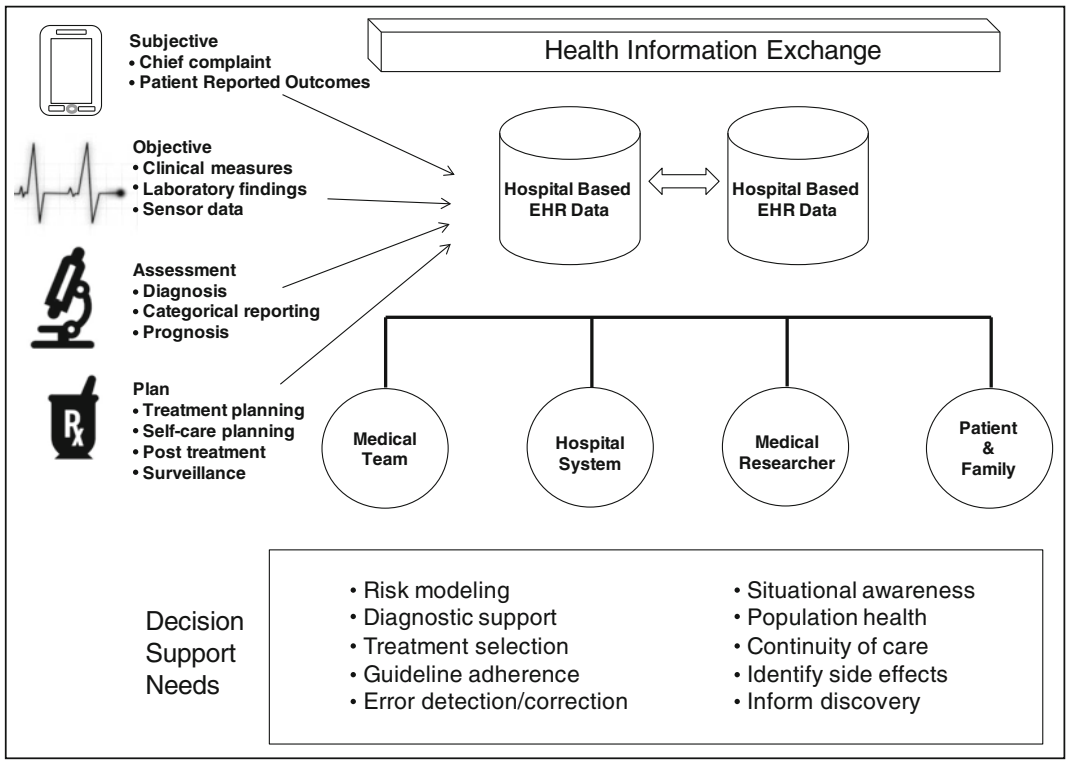

Fig. 2.1 Decision support within a fully connected, data-driven environment of care

is universally rational, logical, and deliberative; while at the same time suggesting how new supports could be constructed within systems to overcome those limitations and improve overall decision-making (Thaler and Sunstein 2009). Hesse et al. 2011 extended the architectural theme into the realm of contemporary health care by examining how a movement toward interconnected data systems could be marshaled to create a robust foundation for evidence-based practice.

Figure 2.1 offers an overview of what an interconnected data system in health care might offer decision makers. Once just a theoretical vision, these types of systems are becoming a reality in many health care systems around the world. In the United States, data from the Centers for Disease Control and Prevention show that adoption of Electronic Health Record (EHR) systems has risen above the 50 % penetration mark among all physicians. Penetration within Health Maintenance Organizations has reached 100 % (Jamoom et al. 2012). At the left of Fig. 2.1 is a depiction of the various types of data signals that are available for compilation within an EHR system. The inputs are organized following the traditional SOAP notes format utilized in paper-based-charts; that is, with *subjective* and qualitative descriptions of the chief complaint included in the record along with *objective* measures from medical tests and laboratory findings, diagnostic conclusions and other professional *assessments*, and ongoing *plan* for treatment and in some cases long-term care or vigilance.

As these data are brought together, they can be made available—separately or jointly—to each of the stakeholders in an expanded view of the care team. According to a literature review sponsored by the Agency for Health care Research and Quality (AHRQ), data at the practice level can be harnessed for clinical decision support to: "(1) remind clinicians of things they need to do, (2) provide information when

clinicians are unsure of what to do, (3) correct errors that clinicians have made, and (4) recommend that clinicians change their plans" as warranted by evidence (Berner 2009). Data at the hospital level can be harnessed by decision makers to: (1) guide quality improvement activities, (2) identify underserved patient populations for specialized outreach, (3) constrain costs, and (4) optimize workflow (Karsh 2009). Medical researchers can use the data to: (1) monitor for post-market side effects, (2) generate hypotheses, (3) update calculations for disease prevalence, and (4) improve the precision of care (McGinnis 2010). Although underappreciated currently, patients should benefit from clinical support around these same data to: (1) participate more directly in shared decision-making processes, (2) formulate more accurate mental models of their disease or condition, (3) improve their self-management skills with accurate feedback on physiological responsiveness, and (4) adhere more rigorously to recommended screening schedules and care plans (Goetz 2010).

Within the Thaler and Sunstein framework, there are six overarching dimensions to consider when constructing improved environments for decision-making. Each will be discussed in the context of a data-enabled, decision architecture as the foundation for evidence-based medicine.

Incentives

Incentives are a core aspect to consider in any view informed by behavioral economics. Understanding what motivates people in their day-to-day decision-making can go a long way in explaining some of the unanticipated consequences of policies or market forces within an economic sector. Berwick's observation that the traditional fee-for-service model may have led to a fragmented and error-prone system of care plaguing the U.S. medical system fits well in this regard. Many health economists have observed that if the current incentive structure is left unaltered it will continue to do even greater harm to patients while bankrupting social safety nets (Cutler 2009). One of the express goals of the Accountable Care Act of 2010, then, was to use the purchasing power of the U.S. Medicare and Medicaid system—one of the largest consumers of medical services—to reassert influence back on the incentive structures in play within the medical marketplace.

Preparatory to passage of the Affordable Care Act, health care economists also noted that the incentives were not in place for medical decision makers to take full advantage of the electronic structures needed to improve care and capitalize on efficiencies (Cutler 2007). Speculations were that in a fee-for-service environment the participating entities who were digitizing records upstream were not necessarily the same parties who would gain maximum return on those investments downstream (Blumenthal 2009). To address this misalignment of incentives, Congress moved in 2009 to pass the Health Information Technology for Economic and Clinical Health (HITECH) Act (Title XIII of the American Recovery and Reinvestment Act). The HITECH Act offered monetary compensation for those who could demonstrate "meaningful use" of health information technologies to improve patient care initially, followed by penalties for failing to use these systems in meaningful ways subsequently in the program. *Meaningful use* was further defined as using Health I.T. to (a) improve the safety and efficiency of health care, (b) to promote patient engagement, (c) to encourage continuity of care, (d) to facilitate population health, and (e) to protect patients' privacy and confidentiality (Blumenthal and Tavenner 2010).

The "patient engagement" component of the meaningful use program resonated with existing research on the importance of patient activation as the first line of defense against chronic and acute conditions (Wagner 2004). University of Wisconsin researchers hypothesized that the health care system could be reengineered explicitly to do a better job at supporting patients' own internal incentives for becoming optimally involved in their own care. What these researchers found was that by adhering to psychological principles of intrinsic motivation (i.e.,

motivations that are internal rather than external to individuals), they were able to engineer decisional architectures to be more naturally empowering to patients. Specifically, the researchers were able to demonstrate greater patient activation by: (a) protecting a patient's sense of decisional autonomy or personal control, (b) offering resources to support mastery of new health behavior skills, and (c) providing a sense of reliable connection to supportive others (Hawkins et al. 2010).

Mental Models

Human information processing succeeds in guiding behavior because it is based on an intricate set of internal knowledge structures, developed both through formal education and through years of experience in complex social environments. These knowledge structures, or schema, serve to organize incoming information, establish parameters for rapid fire decision-making, and set the course for personal action (Morgan 2002). Human factors researchers have noted that many of the decision support structures developed throughout history have been created with the express objective of complementing these internal structures. Whether it was the evolution of human language (which elevated cognition through a system of symbolic abstractions) or the invention of writing, movable type, and now computers the purpose has been the same: to complement "knowledge in the head" with "knowledge in the world" to inform planning, decision-making, and action (Norman 2002; Hesse 2008).

In modern medicine, there are two types of knowledge structures that must converge to influence health outcomes. One is the general knowledge base that the biomedical community brings to the encounter as encapsulated through years of professional training, practice-based experience, and ongoing scientific discovery. The other is an ecologically valid model of the patient's current health condition as informed by the patient's previous health history, self-reports of functioning or chief complaint, physical measurement, and a cumulative set of professional assessments. Medical practitioners come to the clinical encounter imbued with their own, richly articulated mental models for diagnosing problems, for determining courses of treatment, for interacting within the patient-provider relationship, and for following up on care after treatment has been completed (Montgomery 2006). Patients and their families come into the medical encounter with their own "common sense models" of disease organized around understanding what a particular ailment might be, what its cause might have been, what its course (timeline) and consequences might be, and whether there is anything that can be done to control the ailment's outcomes (Cameron and Leventhal 2003). Both practitioners and patients will also bring a rich set of personal values to the encounter, which must also come into play when making decisions (O'Connor et al. 2009).

Much of the design work in decision support has focused on packaging information into a format that is interpretable from the perspective of an intended user's current mental model. Thus, risk communication brochures can be designed to be easily readable by patients with less than a college education and can be written to emphasize the specific links between a risk condition and the actions needed to reduce that risk (Morgan 2002). Information systems perform better when they conform to users' mental models (Shneiderman and Plaisant 2004). Group performance, a criterion of recent attention surrounding the importance of coordinated care teams, improves when the information provided to teams is transmitted in a way that conforms to shared mental models (Salas and Fiore 2004). The idea of using decision support technologies to build a sense of "situational awareness" among team members is relevant here. The goal of enhancing situational awareness is to improve the shared understanding of stakeholders in

a patient's care by representing an ecologically valid model of the patient's history, status, and goals to the full team (Karsh 2009).

Defaults

Most decision architectures carry with them a default course of action, making it easier for users to interact with the system in a timely and cost-efficient way. Employees will either opt-in or opt-out of certain benefit programs at work, depending on the policies set by their organizations. Software users are accustomed to accepting default values when installing their systems or managing upgrades. When set appropriately, defaults can save decision makers a considerable amount of time while providing a course for action that has been calculated to benefit broader societal objectives. Something as simple as building green spaces into the architectural requirements of a new urban landscape can go a long way in making it easy for residents to stay active through walking.

Decision structures in medicine are no different, with default, easy-to-follow paths leading to more implicit endorsement than more effortful options. The difference between default and non-default paths became surprisingly clear to policy makers seeking to improve the rate at which their citizens volunteered to donate organs after death. Some countries have explicit "opt-in" policies for consent to organ donation. In those countries, citizens must go out of their way to indicate their willingness on a consent form to allow their organs to be harvested in the event of a fatal accident. In other countries, the default is different. Citizens are expected to offer their organs for the benefit of others in the event of a fatal accident, and must go out of their way to "opt out" if they are disinclined. Differences in donation rates based on the ways in which these two options are presented are dramatic. In countries with opt-out policies, donation rates usually exceeded 90 % of the population. In countries with opt-in policies, donation rates lingered below 15 % (Davidai et al. 2012).

The problem in modern health care has often been that an inattention to defaults has led to unanticipated negative consequences over time. A default policy suggesting that no one should be offered access to dependency services unless explicitly requested can easily push many would-be quitters away from trying to seek help. The end result is that more costs may be embedded in the system as unattended smoking addictions lead to serious chronic disease for patients in the long haul (Cancer Center Directors Working Group 2006). Similarly, a default hospital culture that makes it difficult for nursing staff to confront physicians about a missing laparotomy sponge upon closing an incision in surgery will increase the likelihood and frequency of medical errors. The consequences can then be terribly expensive, either in financial terms after fighting avoidable litigation or more lamentably in human terms through ruined lives and shattered careers (Berwick 2002). Needless to say, the opportunities for decision scientists to set new, healthier defaults within medical environments are abundant.

Feedback

The idea of integrating feedback into clinical care has been an important part of medicine for decades. It would be hard to imagine a contemporary operating theater that did not provide real time surveillance of blood pressure, O_2 content, heart rate, or operative progress through bioimaging. Ergonomics engineers have worked on these systems to ensure that they optimize team performance by offering continual surveillance of key physiological systems in the background, but then alerting the operating team when values go out of range. Outside of the operating room, precision measurements on physiological status will continue to provide feedback to the care team during post-operative recovery and long term healing. The use of a medical chart to record these measurements over the course of recovery makes it possible for all members of the care team to monitor feedback across situations and over time.

As the medical profession moves towards a model of engaged patient participation, new research will be needed to design the channels and presentations of feedback that can be motivating to patients and their proxies. The "know your number" campaign supported by the National Heart Lung and Blood Institute is a good example of a program designed to help patients keep track of their own cholesterol levels as feedback on their ongoing progress to keep hyperlipidemia in check. Building a record of laboratory tests into a patient's personal health record makes this type of biometric feedback accessible directly to patients as they adjust their diets and behaviors on a day-to-day basis (Krist and Woolf 2011). Psychological evidence suggests that this type of ongoing, biofeedback can be very to motivating to patients as they seek to regulate their own behaviors (Cameron and Leventhal 2003). Evidence from research on successful weight loss programs, for example, suggests that one of the most reliable predictors of dietary success is simply "weighing in" on a routine basis (Goetz 2010).

As the health system begins to record data from a burgeoning set of input channels—from mobile monitoring of input from personal sensors to the systemic integration of electronic health records over a life span—urgent work will be needed to create tools that are empowering and not overwhelming (Hesse and Shneiderman 2007). Hugo Campos, a presenter at a Ted^{X} Cambridge conference and himself a heart patient, illustrated this need in a compelling way. At risk for myocardial infarction, Hugo had received a surgical implantation of a cardiac defibrillator. His specific model, Hugo knew, was sending wireless feedback to his care team. These signals were being interpreted by his care team through a set of well-designed, ergonomically supported decision interfaces. The problem was, (from Hugo's perspective) that everyone seemed to have access to these data except him: the one person who could make a difference in life-and-death decisions about personal activity. After fainting on a train platform, he petitioned to have access to the data, but was initially refused. When he finally did receive the information after much legal wrangling, what was delivered to him was a completely uninterpretable and unusable stack of raw data forms (TedX Cambridge 2012).

With stories such as these, the DHHS Office of the National Coordinator for Health Information Technology has made the transfer of data directly to patients a crucial part of the meaningful use requirements for financial remuneration under the HITECH Act of 2009. Moreover, giving data back to patients for their own consumption is not just a good idea, but according to the DHHS Office for Civil Rights it is an explicit obligation under the Health Insurance Portability and Accountability Act (HIPAA) of 1996. Those will only be useful, however, if they are presented in ways that are comprehensible and actionable for self-management.

Human Error

One of the most fundamental ways in which system designers can use a knowledge of human decision processes to improve the quality of health care is to begin with a scientific understanding of how error occurs, and then create robust architectures to compensate for the potential mistakes people may commit. The "undo" command on most word processing programs is a well-designed example of how software engineers were able to anticipate the situations in which users' writing decisions might lead them down unproductive paths. Other examples include the spelling and grammar checking routines that can help writers avoid common writing mistakes during the composition process along with the dialog boxes requiring users to confirm that an intention to delete or overwrite a file is fully intentional and not the result of a misplaced keystroke (Shneiderman and Plaisant 2004).

When considering ways of preventing errors through decision infrastructures in medicine it is useful to delineate the types of error that are likely to occur. Leap and colleagues aggregated common types of medical errors into four overarching categories: diagnostic errors, treatment errors, prevention errors, and other systemic

errors (Kohn et al. 2000). Diagnostic errors, according to their typology, include errors or delays in diagnosis, failures to employ indicated tests, use of outmoded (and ineffective) tests or therapies, and failures to act on the results of monitoring or testing. Treatment errors include mistakes in the performance of an operation or procedure, errors in treatment administration, errors in administering the dose or method of using a drug, avoidable delays in treatment, or an inappropriate (not indicated or contraindicated) method of care. Preventive failures include a failure to provide prophylactic treatments or an inadequate monitoring or follow-up to treatment. Some of the failures they include in their broad "other" category include failures of communication, equipment failures, or other failures of a systemic nature. When Mazor and colleagues conducted critical incidence interviews with patients, she found that communication errors were especially prevalent sources of complaint from the patient's perspective (Mazor et al. 2012).

Efforts to prevent these errors through a redesign of decision contexts are beginning to show promise. In 2008, the World Health Organization endorsed checklists in set of pilot studies to improve surgical outcomes across cultures. "The magnitude of improvement demonstrated by the WHO pilot studies," according to one author, "was surprising." When implemented correctly, the checklists produced marked improvements in perioperative outcomes and have made significant contributions to patient safety worldwide (Walker et al. 2012). Other innovations that have shown promise in reducing error include the use of physician reminders triggered either by fully functional EHR systems or through paper-based administration records; computerized provider order entry systems (CPOEs), which will reduce variance between providers by offering standardization through pick-lists and by limiting choices to options already justified by evidence; electronic prescribing (eR_X), which can reduce writing/transcription errors while offering a hedge against dangerous drug by drug interactions or side effects; and bar-coded medication administrations (BCMA), which can prevent administration errors at point-of-care while keeping track of usage records across contexts (Institute of Medicine 2011).

Structured Decision-Making

Health-related decision-making is a process. Those involved in the decision process must acquire and interpret inputs, weigh alternatives against probabilities of success, consider course of action in light of personal values, and they must plan, execute, evaluate, and adjust a selected course of action. Patients who experience acute distress must identify symptoms as being out-of-the-ordinary, seek verification of the problem's cause and effect, decide on a course of action, adhere to that course of action until the symptoms and cause are ameliorated, and then take preventive measures to avoid experiencing similar problems in the future. Patients with chronic conditions must extend those processes over longer periods of time, and will need to engage in a protracted period of treatment and self-management. These patients will most likely want to gain an intricate knowledge of their disease so that they can figure out ways of living with it through multiple facets of their lives. They must make daily decisions over what to eat, over how to perform simple activities of daily living, how to work and how to play. They will also need to monitor their own conditions and know when to seek professional help.

Because decision-making is a process, it is useful to consider the ways in which choice architectures can be structured to support better outcomes from that process. Returning to the checklist example, inserting a procedure to evaluate actions against a pre-determined standard of care was an effective way of overcoming error by reorienting the team's attention to a predefined set of steps for effective surgical care. Many of the single-event decision aids for patients documented by the Cochrane Collaboration showed similar efficacy because they shaped a more effective decision process for considering personal values in conjunction with

an understandable presentation of alternatives (O'Connor et al. 2009). On the flipside, decision aids that were not effective often failed to sequence the most important aspects of a decision in a way that was helpful or else created its own demands for structure (e.g., excessive data entry) that was not palatable to users or sustainable to systems (Stead and Lin 2009).

This latter point was reinforced in a review commissioned by the Agency for Health care Research and Quality (AHRQ). In that review, authors concluded that the incorporation of clinical decision supports into processes of care would frequently have a significant influence on overall workflow. In negative cases, the influence on workflow might create a backlog of appointments downstream or may inadvertently draw attention away from important decisional features. In the positive cases, the newly introduced decision architecture could improve workflow. Giving a patient material to read ahead of an appointment, and then reviewing the patients' understanding of crucial points for self-treatment, can work synergistically to promote adherence while making the best use of office time. More importantly, by thinking of shared decision-making as a process that occurs across multiple actors and across multiple settings over time, it is possible to construct new architectures that can improve the overall system of care across multiple interfaces (Karsh 2009).

Conclusion

As demands for precision medicine increase, so too will the needs for new ways of combining personal data with evidence-based recommendations to improve the quality of systemic care. For example, continuous, life sensitive EHRs will be needed to combine personally predictive health information with evolving epidemiologic models of risk to focus preemptive action on targets for primary and secondary prevention. Recorded histories of previous and current treatments can be used to improve pharmacovigilance and to collect valuable post-market data on treatment effectiveness and side effects. Ongoing data aggregation through health information exchanges can be used to improve situational awareness, and improve support for a coordinated mental model of the patient's condition as it evolves over different settings of practice.

A focus on decision architectures in this chapter should serve as a reminder that in the evolving ecology of health care there will be many opportunities for embedding a state-of-the science understanding of decision processes into the environment in which decisions will occur. The perspectives of behavioral economics, which are themselves a compilation of observations from the fields of human factors and social cognition, remind us that it is possible to overcome irrational tendencies and misperceptions by attending to user incentives, mental models, defaults, feedback, human error, and structured decision processes.

Decision Architectures: Implications for Application

Focusing attention on decision architectures changes the administrative vantage point for systems change. Rather than focusing on technologies or policies alone on one hand, or on people and training alone on the other, it recognizes that behavior and context are inseparably linked. Several programs have been retooled with this understanding in mind and present opportunities for action. Two concrete examples are listed below:

- Public Health. The Director of the CDC published a framework for health impact with a goal to "change the context to encourage healthy decisions" listed as a foundational activity in public health. Public health successes in this regard include: healthy defaults for clean air, water, and food; reduction in cardiovascular risk factors by changing from saturated to unsaturated cooking oils; offering healthy choices in school cafeterias over high calorie choices; and promoting smoke-free public place policies.

- Clinical Practice. The decisional architecture approach is beginning to take hold in modern clinical care as practices and hospitals seek remuneration from the Center for Medicare and Medicaid Services for the "meaningful use" of health information technologies. As proposed by advisory councils to the Department of Health and Human Services, the criteria espouse many principles of behavioral economics: that is, they focus on (a) creating a safer environment in which decision-making must occur, (b) promoting patient engagement and system usability, (c) ensuring continuity of care across different actors, (d) managing outcomes at the population level, and (e) building safeguards for privacy and confidentiality.

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