Chapter 1
Cognitive Informatics and Behavior Change in the Health Care Domain

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Abstract The fields of behavioral medicine and biomedical informatics, each with its own theories and methods, have been developing in parallel with little connection until recently. The convergence of research in these disciplines, cognitive informatics, provides enormous opportunities and challenges in addressing the prevention of public health problems and managing disease, as well as in maintaining healthy lifestyles. The limitations of such models in addressing digital health interventions are discussed within the context of cognitive models of behavior and methods of encouraging behavioral change.

Keywords Cognitive informatics • Behavioral theories • Health decision making • Cognitive design • Digital behavior change interventions

The fields of behavioral medicine and biomedical informatics, each with its own theories and methods, have been developing in parallel with little connection until recently. The convergence of research in these disciplines provides enormous opportunities and challenges in addressing the prevention of public health problems and managing disease, as well as in maintaining healthy lifestyles. An article by David Ahern and his colleagues (Ahern et al. 2016), published in a recent book on oncology informatics (Hesse et al. 2016), provides an excellent review of the current status of the merging of these two disciplines, which we summarize below.

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In recent decades, we have seen an explosion in the availability of health information resources. This can be attributed to the Internet coupled with the development of new information management and decision-support technologies. Technology has become a major mediator of behavioral change in our society. It can also provide feedback that allows developers to modify the technology that supports what we do, aimed at reducing the cognitive load that is required as we complete our tasks. The increasing pace of change in recent years is due in large part to the Internet and the use of cellular phones and other technological devices. People can now be in almost constant contact with each other, less dependent on face-to-face communication that occurred in fixed locations. Flexibility in communication has had a dramatic influence on the way that we transfer information, but we need to better understand how this can influence theories about behavioral change. What theories and models do we currently have about cognitive and psychological behaviors that would inform efforts to improve communication and information transfer during transitions in health care?

1.1 Behavioral-Psychological Models

Behavioral-psychosocial models of health behavior have been very helpful in explaining health behavior and how to motivate behavior change. Health behavior models are typically described as a group of psychosocial constructs (such as beliefs, intentions, or knowledge) linked together by relationships (such as causal relationships or associations), with the entire complex predicting an outcome of interest. Readers are referred to Chap. 2 in this volume (Laranjo et al. 2017) for a comprehensive review on behavioral models and outcomes.

An example of a well-validated behavioral model is the Health Belief Model (HBM), an influential theory that does a good job of predicting whether individuals will respond to a health threat by taking preventive or disease-control actions (Becker 1974; Glanz et al. 2008). Health decisions are influenced by *perceived severity* of the threat and the individual's *perceived susceptibility* to it, and the *perceived benefit* of a protective action, *perceived barriers* to action, and *perceived self-efficacy*, that is, the individual's confidence taking the action. Finally, the model recognizes *cues to action*, which are signals directing the individual's attention to their health or the health threat. The HBM and other health behavior models focus on these psychological constructs and their influence on decisions. Some of these constructs reflect perceptions (such as perceived susceptibility to disease). Other models include emotional components. The Extended Parallel Process Model (see Witte 1992; Witte 1998; Witte and Allen 2000 for examples) proposes that the perceived severity and susceptibility described in HBM, together stimulate *fear*, which is a key predictor of whether the individual will take protective action. Researchers and practitioners seeking to understand health decisions administer questionnaires or interviews to capture these constructs and link them to decisions. For example, for a Spanish-language mobile app for diabetes self-management, Burner and colleagues conducted interviews to show that the text messages are important not because they educated people about previously unknown diabetes facts, but because they served as cues to required action under the HBM (Burner et al. 2014).

However, these models also have limitations stemming from the fact that they do not address the cognitive processes by which individuals collect information, think about it, integrate it with their existing beliefs and knowledge, and act upon it.

As a simple example, the HBM and the Extended Parallel Process Model recognize that our decisions are influenced by our evaluation of the possible outcomes of the decisions—so, for example, whether we get a flu shot is influenced by our perception of the risk of flu and the effectiveness of the shot. But neither model acknowledges that the ability to collect information and assess risks is shaped by health literacy and health numeracy. Individuals with low health literacy may have limited ability to read and process information about the flu, whereas individuals with low health numeracy often develop exaggerated perceptions of risks (Ancker and Kaufman 2007). These cognitive factors shape all of the constructs, relationships, and processes in health behavior models. Failing to account for them can lead to intervention failures, such as when people are unlikely to act upon a flu promotion message designed to be "cue to action" if it is written at a high reading level full of medical jargon.

Another example can be found in electronic patient portals, which gives patients access to their medical records and have become increasingly common internationally. Unfortunately, it is also increasingly clear that portals are ill-suited to the cognitive needs of their patients. Britto and colleagues show that even though electronic patient portals contained potentially invaluable information about children's health and healthcare, the parents have difficulty locating this information because of poor system usability (Britto et al. 2009). In our small ongoing usability project, we similarly found that only 2 out of 15 patients observed using the portal were able to successfully export their medical records to share with other doctors (Ali et al. 2016). From analysis of their think-aloud protocols (a well-known cognitive psychology method of data collection), it was evident that the visual design of the portal was not clear enough to help patients to construct a coherent schema (or mental model) of the portal. In part due to this problem, most patients could not develop a successful mental representation of the sequence of actions they would need to execute in the portal to accomplish the task (Patel and Kaufman 2013). However, interestingly, a number of patients developed creative and idiosyncratic solutions to accomplish the goal by exploiting other portal affordances. These solutions included cutting and pasting elements of the record into a word document, taking notes or even screenshots, or sharing their password.

These limitations of portals demonstrate the dangers of failing to consider the cognitive aspect of human behavior. If patients cannot access information and functions of the portal because of poor design, then it is unlikely the portal could successfully be used to deliver a theoretically-grounded behavior change intervention. When we recognize these limitations, we open the door to more powerful ways of thinking.

1.2 Cognitive-Psychological Models

Models of cognition reflect the generality of cognitive processes and they have not been developed specifically for the field of health. This generality supports the assumption that the cognitive architecture and processes are universal characteristics of the human mind, and are relevant to any given area or domain, either formal or informal. Models of cognition have also been used to account for various behaviors, such as those involved in decision making and problem solving. Thus, making use of a cognitive approach allows researchers and practitioners access to a breadth of scientific information that covers many different content areas and theories of cognitive processes beyond health and medicine.

Research in a variety of non-health and health-related areas (see Patel and Kaufman 2013; Patel and Kannampallil 2015; Patel et al. 2001 for a review) revealed the role that these cognitive processes play in problem solving and decision making, while stressing learning and performance as a function of domain knowledge. Knowledge, its content as well as its organization, has shown to be critical in a variety of tasks, including domains ranging from chess, to basic physics, to medicine and health (Patel et al. 2002, 2000a; Chi et al. 1988). Given the central role that knowledge plays in cognition, a basic assumption about research on health is that people, including the specialist as well as the non-specialist, intuitively interpret information in terms of their own prior beliefs, backgrounds and assumptions. Such intuitions are often in conflict with scientifically acceptable knowledge. Being aware of the discrepancies between intuitive models and scientific information is especially important in understanding the ways people assess health risk and, indeed, about risk in general. For instance, Arocha and Patel (1995) show that when dealing with information that is inconsistent with prior beliefs, people's interpretation of the said information is a function of their knowledge structure and organization, more than the amount of factual information. Similarly, a study (Patel et al. 2000b) that investigated the reasoning that mothers in rural South India employed to account for the cause and treatment of childhood malnutrition indicated that intuitive and traditional folk knowledge of Indian medicine mediated their health practices. Such knowledge was found to be story-like and was coherent with the mothers' causal explanations, suggesting globally coherent knowledge structures. Furthermore, when modern, scientific, medical knowledge was used, it remained compartmentalized and separate from the traditional knowledge, lacking the narrative structure and coherence of intuitive health knowledge. In addition, traditional knowledge continued to exert considerable influence on their reasoning.

The nature and organization of knowledge has implications for behavior change because any interventions can be matched to the familiarity with health domains that people have. Beliefs associated with coherent knowledge structures can be difficult to change if such knowledge is not taken into account; thus, rather than attempting to replace traditional knowledge, a more effective strategy could be to connect the new knowledge to the old knowledge while maintaining as much of the narrative nature and coherence of health knowledge structures as possible.

1.3 Conceptual Understanding and Health Care Decisions

Research in the health-related domain has suggested that having the knowledge alone is not enough for behavior change (for example, Sivaramakrishnan and Patel 1993; Chan and Chin 2017) and it is generally accepted that knowledge is a necessary, but not a sufficient condition for behavior change (Kenkel 1991). However, in the majority of the studies about behavior and knowledge, the latter is conceived as a collection of "facts" in people's memories. However, knowledge of "facts" is only one of the ways knowledge can be conceptualized. Indeed, there are different forms of knowledge that vary in terms of their degrees of depth. For instance, the knowledge possessed by the expert is of a different quality than that of the naïve or novice person as it goes much beyond the "factual" knowledge investigated in behavioral research. This has implications for designing tools for supporting communities with different levels of literacy.

The theory of conceptual change (Kaufman et al. 2013) posits that people's prior knowledge influences their beliefs and the generation of new beliefs, and that real understanding is required for true conceptual change, something which the simple accumulation of "facts" cannot produce (Kenkel 1991). Research suggests that a deep understanding of health concepts can lead to changes in health practices (Kenkel 1991; Vosniadu 2013). Also, investigation and assessment of conceptual change shows that underlying people's attempts to understand health concepts includes a variety of misconceptions that need to be identified and explicitly addressed in order to foster changes in making better decisions, and therefore better choices in health behaviors. Among the benefits of conceptual change is a kind of cognitive flexibility that allows a person to adapt knowledge to a variety of different contexts leading to a higher level of understanding (Donovan and Ward 2001). Such flexibility is a function of the in-depth nature of genuine conceptual understanding.

Finally, cognitive-psychological research that focuses on cognitive processes underlying decision making (role of memory, knowledge strategies and inferences) play a major role in determining how well any decision support systems deliver information that is received and processed, and action taken the way the designers intended them to. The deployment of electronic health record (EHR) systems in hospitals and through health care systems and healthcare clinics have contributed to the advancement of computer decision support at the point of care, and patient portals are being introduced such that physicians can engage patients so that they are more informed about their own delivery of healthcare. This also facilitates better communication between clinicians and patients in the decision making process. Recent mobile health technology (e.g. smart phones, iPad tablets, social networks), as a well as the use of sensor-based technology (e.g. wearable devices such as Fitbit, which uses physiological sensors, Bluetooth Beacon; radio frequency identifiers), has been used to communicate and monitor health-related behaviors. These mobile apps and other digital health care tools hold great promise as interventional methods to improve the health and wellbeing of an individual. The behavioral sciences, including cognitive sciences, offer ample evidence that we can leverage the principles from these sciences to advance the development and deployment of technological tools to provide efficient, effective and safe care to the patients.

1.4 Theories, Models and Frameworks

Behavioral change theories are attempts to explain why and how behaviors change. These theories cite environmental, personal, and behavioral characteristics as the major factors in behavioral determination. There are two major distinctions between the models of behavior and theories of change (Coulson et al. 1997). Whereas models of behavior are more diagnostic and geared towards understanding the psychological factors that explain or predict a specific behavior, theories of change are more process-oriented and are generally aimed at changing a given behavior. Thus, from this perspective, understanding and changing behavior are two separate but complementary lines of scientific investigation.

Theories have abstract and generalizable concepts with explanatory power, which specify relationships among constructs. Theories also follow a deductive system of logic for interpreting few empirical data that can either support the theory or provide evidence for its inadequacy. In contrast, conceptual frameworks share all the features of theories, except that they do not have explanatory power or follow a deductive system of logic (Patel and Groen 1993).

Theories of behavior change have been variable and tend to emphasize group-level generalization, although a theory is capable of generating individual behavioral patterns. A good theory will provide both group-level and individual-level generalizations. Digital behavior change interventions (DBCIs) are interventions that employ digital technologies to encourage and support behavior change that will promote and maintain health, through primary or secondary prevention and management of health problems. The readers are referred to a recent paper on Advancing Models and Theories for Digital Behavior Change Interventions (DBCIs) which provides an excellent account of limitations of behavior theories and future directions for research (see Yardley et al. 2016; Hekler et al. 2016). The authors argue that theories are key to personalization of DBCIs. Theories also facilitate health promotion by providing support in the "real world" to change-focused behaviors in specific contexts, and are used by individuals (Hekler et al. 2016). DBCIs use information about an individual to provide support in changing needs of the individual over time. Pagoto and Bennett (2013) argue for a critical role of behavioral and psychological science in advancing digital health and digital interventions. Furthermore, given the nature of expertise and limited funding resources, behavioral science researchers and industry that develop technological innovations cannot afford to work alone or in parallel to one another, but need to work in a team science approach with a multidisciplinary work.

1.5 Future Directions

We are in the midst of a transition from a focus on disease and its management to an effort to promote healthy lifestyles and activities that will help to stave off disease and provide a sense of wellbeing to individuals. This transition requires an increasing focus on cognitive aspects, not only in an individual's response to disease but in the way that they perceive and seek health. This suggests an increasing focus on cognitive design (design coupled to a way of thinking), which has implications both for an individual's response to disease and for their pursuit of health and its maintenance.

The multifaceted elements that underlie behavioral change imply that multidisciplinary collaborative research is needed. Basic principles from cognitive-behavioral and psychological sciences offer many opportunities to leverage cognitive informatics in developing behavioral support tools. Disparate theories and models of behavioral change can be reconciled with the creation of robust behavioral ontologies that allow the identification of how the general notions might apply to a specific individual. Current models of behavior focus on group-based outcomes, but with better development of strong theories, we will see a move towards addressing the evolution of personalized health, reflecting behavioral changes and their gradual or acute impact on the individual (Ahern et al. 2016; Yardley et al. 2016).

Technology is increasingly considered not to be separate from the healthcare team but, rather, to be a part of it. The resulting "intellectual partnership" can provide support in any patient-centered collaboration. The team must work together within the care system to ensure that the patient is not 'dropped' (Patel and Crook 2014). Although advances in communication technologies will enhance team effectiveness, we need to make sure that such influences are also scalable over time as teams increase in size or the number of patients that they manage.

The complex nature of clinical care and health promotion can make it difficult to measure the influence of technological behavioral interventions. In most healthcare systems, situations change incrementally but non-linearly, with changes in focus due to multitasking and constant interruptions. Given that we are destined to function in such a world, and that the interventional technology itself is complex, any good design should attempt to tame complexity as much as possible, but learn to manage that which is untamable. As an example of why such complexity and its management is important, Donald Norman, in his book *Living with Complexity*, discusses two aspects of understanding that are considered pertinent for successful interventions (Norman 2010). These include understandability (i.e., once we understand the logic and underlying structure, many uncertain aspects make sense) and understanding (i.e., we must give enough time and effort in order to develop our own set of abilities and skills for understanding the structure). Models or approaches that fail to recognize such distinctions are doomed to fail; simplistic models fail to provide useful approaches for tackling such problems in real-world settings such as those that characterize the world of medicine and health (Kannampallil et al. 2011; Patel 2014).

This book accordingly acknowledges the complexity we have outlined and proposes a number of methods and examples for tackling real world problems in which simplistic solutions are certain to fail. The focus is on behavioral issues and the role of both technologies and cognitive theory in assuring that effective changes in behavior can be encouraged and measured.

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