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# ALIGNING INFORMATION TECHNOLOGIES WITH EVIDENCE-BASED HEALTH-CARE ACTIVITIES: A DESIGN AND EVALUATION FRAMEWORK

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Abstract: *Evidence-based health care (EBHC) has given rise to expectations that decision-making be tethered to more high-quality information. As health information technologies (HITs) acquire an increasingly vital role in the information processes involved in EBHC, a more mature understanding is needed of the relationship between HITs and the EBHC activities they serve. In this paper, we conceptualize HITs and EBHC activities on a common foundation of distributed cognition that treats humans, technology, and the environment as interwoven parts of a whole, dynamic system. From that common foundation, we articulate a basis for achieving a contextually sensitive fit between HITs and EBHC activities by providing a framework (DETECT) of 20 properties that can be used to systematically characterize the fit between HITs and EBHC activities. Designers, deployers, and evaluators of HITs can use DETECT to better anticipate, locate, and diagnose the issues that arise when HITs are used to achieve diverse EBHC commitments.*

Keywords: *health information technology, evidence-based medicine, distributed cognition, integration, health-care activities.*


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## INTRODUCTION

Health-care practice is fed by more information from a wider range of sources than ever before. Although this presents a great opportunity, the task of better integrating this information into the diversity of activities that make up health care can be a difficult one (Straus, Tetroe, & Graham, 2013). Researchers in evidence-based health care (EBHC), perhaps the most influential force reshaping the use of knowledge and information in contemporary health care (Mykhalovskiy & Weir, 2004), aim to facilitate the use of the best available scientific information to ensure the most appropriate decision-making. EBHC stakeholders (e.g., health practitioners/workers, policy-makers, public health managers) aim to improve health-care outcomes, clinical practices, and efficiency and effectiveness in health-care delivery. Toward this end, EBHC research concerns a range of issues, including (a) summarizing the methods and criteria to rank research (Glasziou, Vandenbroucke, & Chalmers, 2004; Woolf, Schünemann, Eccles, Grimshaw, & Shekelle, 2012), (b) training stakeholders in the skills required to appraise and employ the evidence (Greenhalgh, 2014), (c) developing and updating infrastructures for evidence-based guidelines (Hill, Bullock & Alderson, 2011), (d) clarifying the nature and scope of evidence (Charon, 2006; Goldenberg, 2006), and (e) explicating the relationship of evidence to its context of use (McNutt & Livingston, 2010; Weiner, 2004).

In recent years, researchers contributing to a growing body of health information technology (HIT) literature also have begun to explore how technological advances can be leveraged to contribute to the EBHC agenda (Rodrigues, 2000; Timsina, El-Gayar, & Nawar, 2014). Because HITs provide the means to acquire, appraise, and apply the evidence central to EBHC, they play a pivotal role. Thus, HIT researchers occupy themselves with a wide range of concerns, including:

- The use of automated tools for evidence generation, distillation, or synthesis (Cohen et al., 2010; Kim, Martinez, Cavedon, & Yencken, 2011),
- The integration of evidence across multiple computational sources (O'Sullivan, Wilk, Michalowski, & Farion, 2010),
- Decision support for incorporating evidence-based protocols into clinical workflow (El-Kareh, Hasan, & Schiff, 2013; Sim et al., 2001),
- Standard clinical vocabularies to ensure understanding among systems (Sim, Sanders, & McDonald, 2002),
- Web-based platforms to facilitate physician-patient communication (Swan, 2012), and
- The technological bases for institutional learning and improvement (Abernethy et al., 2010; Bigus et al., 2011).

Despite the shared interests between the EBHC and HIT communities, there is a fundamental disconnect between the two. On the one hand, the dominant conception of EBHC activities assumes that these activities can be defined and understood without reference to the constitutive role that HITs play. For example, models of evidence utilization (Graham & Tetroe, 2007; Green, 2006) tend to portray the generation, synthesis, and tailoring of evidence as an exclusively human-driven activity, without regard for how HITs filter, process, and display that evidence. On the other hand, HIT researchers seek to address EBHC issues by focusing on technical considerations, dealing with the fundamental nature of information and evidence primarily as a peripheral issue. For example, the efforts toward creating contextually sensitive decision-support systems rely on overly simplistic algorithmic aspects of clinical reasoning and workflow, while the need to support clinical decisions within a dynamic information ecology remains an underdeveloped area of study. We contend that, in order to truly seize the opportunity of better integrating information into EBHC activities, this disconnect must be overcome and greater movement towards harmonization must be made by both researchers and practitioners. Specifically, more must be done to understand the dynamic and distributed context within which stakeholders and HITs interact and cooperate with one another to create and utilize evidence. Parallel with the growth of health-care knowledge, there is a proliferation of HITs (particularly health informatics tools) in the health-care industry. EBHC activities are becoming increasingly dependent on both knowledge as well as HITs. A more nuanced understanding of the relationship between HITs and EBHC activities is becoming increasingly vital. Without a clear understanding of how to conceptualize the relationship between HITs and EBHC activities, a design and evaluation gap exists that limits the effectiveness of HITs in supporting these activities. The purpose of this paper is to contribute to the bridging of this gap.

In this paper, we propose a framework, DETECT (**D**esign and **E**valuation of HI**T**s for **E**BH**C** Ac**T**ivities), to help with the systematic design and evaluation of HITs to better support the relationship between health-care stakeholders and HITs in the execution of EBHC activities. Three assertions lay at the foundation of our approach. Firstly, while it is increasingly common to see dynamic, relational, and contextually sensitive approaches to knowledge in health care (Nicolini, Powell, Conville, & Martinez-Solano, 2008), these approaches are less common in research conducted from information and cognitive lenses. Rather, dynamic and contextual approaches tend to be sociological, political, or ethical in outlook, while cognitive approaches often retain the individualism, rationalism, and determinism of more traditional research (Hutchins, 1995; Patel, Kaufman, & Arocha, 2002). In this paper, we are committed to exploring cognitive and information phenomena in a dynamic, contextual way. Secondly, the lack of use of cognitive and information-processing perspectives in understanding the human and relational aspects of HITs in EBHC has its ultimate root in the tendency of cognitive science to strip away the body and environment from any active role in information processing (Clark, 2008). In this paper, we discard the traditional dichotomies among mind, body, and environment and, using the theory of distributed cognition, foreground how relationships among these components enable and support the information processing that underlies dynamic EBHC activities. Thirdly, while many researchers have explored empirically the utility of HITs in diverse health-care settings (e.g., evidence-based health informatics; Ammenwerth & Rigby, 2016), a paucity of research remains regarding attempts to contextualize those findings within rigorous theoretical frameworks that encourage systematic analysis of HIT–stakeholder relationships. In summary, the use of HITs to serve the goals of EBHC remains theoretically underdeveloped and lacking in generalizable principles that would allow researchers, designers, and evaluators of HITs to systematically analyze and implement HITs with optimal support for EBHC activities. In this paper, we lay out the DETECT framework of factors to assist those who design, deploy, or evaluate the integration of HITs into EBHC activities and settings.

The balance of the paper is laid out as follows. We begin by investigating the conception of activities found in the EBHC literature by reevaluating the emphasis placed on behaviorist and traditional cognitive conceptions of EBHC activities and recasting them in light of their reliance upon distributed, dynamic, contextual, and emergent cognition. After discussing the characteristics of EBHC activities, we turn our attention to examining HITs, specifically the difficulties associated with integrating HITs into EBHC activities, partly because of conceptions that obscure their relationships to their environment. This work allows us to articulate a basis for systematic conceptualization of the relationships that bind HITs to stakeholders in EBHC activities. In the last section of this paper, we present DETECT, a framework of general factors that researchers, designers, and evaluators of HITs can use to systematically analyze HIT-stakeholder relationships in the service of seamlessly integrating HITs into EBHC activities.

## EBHC ACTIVITIES

EBHC activities rarely are the result of a single stakeholder thinking and acting in seclusion from others or without the aid of external artifacts. Most EBHC activities are dynamic, contextually sensitive, and achieved through the stakeholders and artifacts working in unison. In this situation, information moves back and forth between various stakeholders and artifacts, in different places, and through a variety of media. Consider a team of emergency room practitioners performing a targeted assessment to stabilize a heart attack patient upon her admission. The team will need to obtain vital signs, a medical history, a complete physical exam, several test results, information derived from a variety of sources, including the patient or family, the hospital medical record database, an x-ray machine, and the clinical lab. The information used to stabilize the patient is diverse and variable. The patient assessment and treatment are the result of the coming together of all of these sources of information. To look at each of these information sources as independent entities obscures the dynamic interdependence of the information and the necessary relationships that bind them together in enabling the best decision at the right time.

At its heart, EBHC is intended to help various stakeholders perform activities aimed at making the right decision at the right time. EBHC relies on the deliberate, conscientious, and systematic use of available evidence in diverse activities and settings to improve health care. Evidence in this context can refer to knowledge and information in a variety of forms: the current best scientific research evidence, practitioner expertise and judgment, patient narratives (Charon, 2006), and/or other contextual factors (such as cultural or traditional knowledge; Brownson, Baker, Leet, Gillespie, & True, 2010). Writ broadly in this way, EBHC activities encompass all practices, behaviors, and skills that rely explicitly on information and knowledge across all areas of health care (Gray, 2010).

In today's EBHC climate, activities are more information- and knowledge-intensive than ever before. The characteristics of the information that those activities rely on (e.g., its scope, its quality, and its inherent subjective or objective properties) are, in themselves, factors in shaping those activities. Hence, whether an activity is evidence-based will depend partly on the characteristics of the information that it relies on. For example, the process of safely administering some vaccines, while a relatively simple practice, can require extensive knowledge about the factors that may predispose a patient to an adverse reaction, the characteristics of the infectious disease, and social and demographic information about its spread. Making an evidence-based decision to vaccinate or not must be done within a context that integrates these different sources of information into an apt solution, a process that rarely follows a linear formula. In short, EBHC activities increasingly rely on the appropriate and effective use of high-quality information and knowledge, and assessing whether a decision is evidence-based requires evaluating it in the context of the characteristics of the information used to support it. Because of this, EBHC activities and the information on which they rely are best understood as connected and associated, rather than analytically separate.

Supporting EBHC activities, then, calls for an understanding of how the characteristics of information shape activities in dynamic EBHC contexts. Until now, however, the EBHC community has not been centrally concerned with considering the characteristics of information and the relationships that bind information to its environment. Rather, implementation of EBHC has tended to focus on the categories or types of information needed for health care, the methodological rigor with which that knowledge is produced, or the skills and practices that allow stakeholders to access it (Sedig, Parsons, Naimi & Willoughby, 2015). Alternately, some attention in the EBHC community has been directed toward the cultural, ethical, or political issues involved in using evidence (Holmes, Murray, Perron, & Rail, 2006). Although these are important factors in successfully employing EBHC, they do not represent the full reality. These approaches stop short of spelling out the implications for how information is integrated and used in dynamic EBHC activities. This failing results in the treatment of EBHC activities in the literature as sterile and lacking nuance. Thus, the presentation here of our survey of some of the common conceptions of EBHC activities provides a useful tool in advancing the goal of closely integrating the human, experiential, medical, technological, and contextual components contained in EBHC activities.

Perhaps the most common misconception is that EBHC activities are primarily a behavioristic enterprise, that is, rooted in tasks. EBHC activities typically are seen as observable or measurable skills and practices, such as teaching physicians the skills to conduct evidence-based inquiry or decision-based interventions aimed at supporting clinical workflow (Greenhalgh, 2014). Associated with this, EBHC activities often are conceptualized in functional, utilitarian, or goal-centered ways, that is, what users do, rather than what users know or should know. As a result, the approach to these activities bypasses the role of information or cognitive dynamics. Thus, this view tends to take a post hoc view of tasks built upon assumptions that the steps to task completion can largely be specified a priori. Here, the ends supplant the means, and analytical primacy is given to the outward and observable aspects of task execution. For example, the labels “decision-making tasks,” “diagnosis tasks,” or “data collection tasks” do not describe the inner workings of how those activities are accomplished, but rather the outcome or product of task accomplishment.

Moreover, even when information and cognition are figured into the analysis of EBHC activities, they tend to be derived from traditional psychological and economic models of decision-making (Bucknall, 2007) that misrepresent cognition as individualistic, rationalistic, and objective (Hazlehurst, Gorman, & McMullen, 2008; Patel et al., 2002; Sedig et al., 2015). Researchers working from the perspective of traditional cognition tend to treat information processing as a purely mental phenomenon and overemphasize the normative, universal, and systematic aspects of human thought. In EBHC, this view directs the attention of those implementing and supporting EBHC activities to the predictable, context-independent, and mechanistic aspects of information use, which are assumed to be executed in much the same manner regardless of the activities they serve, where they are carried out, or the stakeholders engaged in the activity. For example, the tendency to reduce EBHC activities to the mere access of explicit and precodified medical evidence assumes that the cognition used to process that information is itself linear and predictable (Sedig et al., 2015).

Beyond the purely theoretical problems associated with existing conceptions of EBHC activities, there also lies the practical mismatch between those conceptions and the information needs of the modern health-care system; that is, despite the prevailing emphasis in EBHC on information processing that is linear, objective, rational, and predictable, many health-care situations are unpredictable, ill-structured, or defy standardization (May & Ellis, 2001; Timmermans & Berg, 2003). In these cases, evidence, guidelines, or protocols may be unavailable, only indirectly relevant, and/or require extrapolation or other transformations to be useful, leaving the stakeholders to rely heavily on their own unaided judgment (Bohmer, 2009; Green, 2006). For example, in formulating public health policy to address the rising tide of childhood obesity, where little research exists, policy makers may need to use information and evidence whose import does not bear directly on the present problem. Then they will need to make nuanced judgments and interpolations, with no prespecified rule or guideline to guide the process, in order to extend evidence from other policy situations to the current problem.

Ultimately, the problems associated with conceptualizing EBHC activities can be traced to the philosophical orientation of brain–body dualism (Clark, 2008) built upon the assumption that cognitive activities can be understood and supported without a holistic understanding of how the brain, environment, and body work together. Conceptualizations of EBHC activities borne of this position tend to be linear and rationalist because it is assumed that the information and knowledge required to perform any EBHC task can be accounted for with reference to the mental states of the stakeholder(s) in isolation from the context or environment. In contrast, in this paper we suggest that the execution of EBHC activities relies on information processing achieved through a reciprocal relationship among mental, behavioral, and environmental phenomena. In the next section, we elaborate on the theory of distributed cognition as a platform from which to dissolve the underlying linearity of traditional approaches to EBHC activities and systematically investigate the holistic relationships among the brain, body, and environment. This process serves as a precursor to proposing the conceptual framework, DETECT, for better aligning EBHC practice with HITs.

## EBHC ACTIVITIES WITHIN DYNAMIC AND DISTRIBUTED COGNITIVE SYSTEMS

### Distributed Cognition

The theory of distributed cognition allows for investigating how information and knowledge are used in real-world settings (Hutchins, 1995). Two fundamental assumptions in the theory are that no division exists among the brain, body, and environment and that cognition results from several information sources and channels working together. In health care, distributed cognition has been used to understand the cognitive dynamics underlying medical communication and collaboration (Hazlehurst, McMullen & Gorman, 2007; Hazlehurst, McMullen, Gorman & Sittig, 2003; Nemeth, Nunnally, O'Connor, Klock & Cook, 2005), the various issues related to medical tools and technologies (Horsky, Kaufman, Oppenheim & Patel, 2003; Nemeth et al., 2005, Xiao, Schenkel, Faraj, Mackenzie & Moss, 2007), medical education (Bleakley, 2006; 2010), and medical decision-making (Patel et al., 2002).

### Cognition as Distributed and Contextual

Real-world cognition is not the exclusive product of processes internal to an individual's brain, but rather the result of dialectical interaction, coordination, and alignment of the multiple information resources embodied in the body, brain, physical and social environments, and time. As such, the relevant unit of analysis for cognition is not the individual, but rather the "activity system" that comprises the human beings, the artifacts, and the objects in the environment that contribute to the performance of a cognitive activity (Hazlehurst et al., 2008). Cognitive activity, comprising of subactivities, tasks, subtasks, and lower level actions, is an emergent phenomenon, resulting from a number of ongoing relationships between information-bearing structures and processes working harmoniously within an activity system, and thus cognition cannot be understood by examining any one of these pieces in isolation (Sedig & Parsons, 2013).

### Cognition as Emergent

Cognitive activities can be described as either simple or complex. Simple cognitive activities are typically elementary processes, such as perception and memory, which can be carried out independent of any specific environment or context (Funke, 2010) and tend to follow a linear, predictable progression. For example, a physician typically can recall many basic medical facts from her[1] long-term memory in response to a situation requiring such information (Ericsson & Kintsch, 1995). Complex cognitive activities, on the other hand, are the emergent product of multiple instances of simple cognitive processes, such as sensemaking, decision-making, learning, planning, and problem solving (Sedig & Parsons, 2013). Knauff and Wolf (2010) identified two characteristics of complex cognitive activities. Firstly, such activities rely on other cognitive processes, such as perception or memory, for their execution. Secondly, they occur in complex conditions. Cognition is complex when it is generally unstable, unpredictable, or impossible to understand without a sense of the broader conditions of its execution. For example, sensemaking may be complex when the information being used is intractable, the activity difficult to initiate and comprising many other tasks and subtasks, or the other variables involved exhibit a high degree of interdependence (Funke, 2010; Knauff & Wolf, 2010; Sedig & Parsons, 2013).

### Cognition as Dynamic and Ongoing

Another important implication of distributed cognition is that complex cognition is dynamic and ongoing. Evidence is not a fixed trait, capability, or resource, but rather an ongoing accomplishment that must be constantly reconfigured in light of changing conditions (Orlikowski, 2002; Sedig et al., 2015). Because the interactions among all the factors that bear upon cognition are unpredictable, the cognition underlying EBHC activity is nonlinear and unpredictable, and its outcome or performance can never be specified beforehand (McClelland, 2010). From the perspective of distributed cognition, EBHC activities are contextually realized accomplishments that involve the alignment or coordination of various sources of information brought together in the context of an activity system to accomplish specific EBHC goals and tasks. These sources of information undergo iterative transformations through processes carried out via diverse media, including stakeholders and HITs.

In summary, there exists a clearly dynamic, distributed, and emergent character of EBHC activities and, because HITs nowadays play such a vital role in EBHC executions, our concern here is to understand how HITs can be properly aligned with and seamlessly integrated into EBHC activities. Before we discuss how HITs and stakeholders can be understood to work together in the context of EBHC activities, we briefly address the various conceptualizations of HITs that act as barriers to fully understanding how they participate in dynamic EBHC activities.

## CONCEPTUALIZING HEALTH INFORMATION TECHNOLOGY

HITs have not received sufficient attention in the EBHC literature. Despite the different origins and distinct concerns of the two research communities, today the situation is such that the goals of EBHC cannot be adequately discharged without the assistance of HITs. HITs mediate EBHC activities at every turn, yet the mainstream EBHC community remains content to leave HITs as an invisible and unacknowledged substrate upon which EBHC activities rely. In this context, fostering alignment between HITs and EBHC activities is rife with difficulties, as evidenced by the varying degree of success that accompany programs of HIT implementation. For example, the use of HITs in health care often has been characterized by low adoption rates (DesRoches et al., 2008; Jha et al., 2009), misuses, and unexpected failures (Ash, Sittig, Dykstra, Campbell & Guappone, 2009; Karsh, Weinger, Abbott & Wears, 2010). Incongruous use of HITs also can lead to a decline in the quality and safety of health care (Linder, Ma, Bates, Middleton & Stafford, 2007; Zhou et al., 2009), enable faulty decision-making and miscommunication (Niazkhani, Pirnejad, Berg & Aarts, 2009), and give rise to new potential for medical errors (Koppel et al., 2005). In the remainder of this section, we discuss the limitations of four common conceptualizations of HITs and, in the following section, highlight the active information-processing role that HITs play within EBHC activities.

Confusion abounds in the literature about how to conceptualize and define HITs. The problem, although applicable to all HITs, is well illustrated through efforts to define the electronic health record (EHR). Consider, for example, the following statements: "According to the literature, the meaning of EHR is unstable. An EHR has many functions and includes many kinds of data, and it is obvious that there is a need to determine explicitly what EHR means" (Häyrinen, Saranto & Nykänen, 2008, p. 292). Adler-Milstein and Bates (2010) agreed: "There has historically been little agreement on what type of IT system meets this definition [of EHR]" (p. 122). Attempts to define EHRs are generally either too vague to be meaningfully distinguished from other tools or rely on decomposing the system into its functional components, offloading the burden of definitional clarity onto the tools or systems of which they are composed (Jha et al., 2009; Tang & McDonald, 2006). The same problem exists in relation to other HIT systems (Tang & McDonald, 2006), including all new and emerging health informatics tools for the age of big data (Andreu-Perez, Poom, Merrifield, Wong, & Yang, 2015; Fang, Pouyanfar, Yang, Chen, & Iyengar, 2016; Tresp et al., 2016). As a result of this lack of clarity surrounding HITs, it is naturally difficult to understand exactly in what sense HITs can support or improve the quality of EBHC activities.

In general, there are four ways in which HITs are understood to contribute to health-care activities. Firstly, HITs can be categorized in a system-centered way. For example, they can be classified in terms of the system specifications, hardware, or software. Secondly, HITs can be categorized according to the operational or disciplinary context in which they are used. For example, they may be understood from the perspective of clinical informatics, public health informatics, nursing informatics, imaging informatics, or consumer health informatics (Barrett, Liaw, & de Lusignan, 2014; Demiris, 2016; Hersh, 2009; Moen & Knudsen, 2013; Shortliffe & Cimino, 2006). Although these sorts of classifications serve to highlight the unique disciplinary differences in the application of technology, they fail to highlight the aspects of HITs that transcend disciplinary boundaries and the role they play in supporting the actual information flow that underlies EBHC activities. Thirdly, HITs have been categorized in terms of their functional capabilities (Faraj & Azad, 2012). Functionality-centered definitions treat HITs in terms of the type of operational goals or tasks that they intend to support (Adler-Milstein & Bates, 2010; Tang & McDonald, 2006). For example, EHRs are defined as such because they support clinical documentation and results management, computer-order entry systems are labeled as such because they support order-entry management, and so on. Looking at HITs in terms of their taken-for-granted features fails to account for the diverse ways they are actually used (Leonardi & Barley, 2010; Orlikowski & Iacono, 2001), pays inadequate attention to the role that HITs play in the dynamic use of information, and provides an insufficient foundation for the design of HITs (Woods, 1998). The result of this misalignment between the actual necessities of EBHC activities and individuo-centric cognition is that HITs are bound to fail, or at least unleash a host of unintended consequences (Ash, Berg & Coiera, 2004; Campbell, Sittig, Ash, Guappone & Dykstra, 2006; Koppel et al., 2005), because the assumptions of the psychology of work inscribed in HITs clash too much with the actual nature of real-world EBHC activities (Berg, 2004; Li, 2010; Niazkhani et al, 2009; Wears & Berg, 2005). Fourthly, and finally, knowledge-centered definitions classify HITs according to the knowledge processes they support (Newell, Robertson, Scarborough & Swan, 2009). For example, Alavi and Tiwana (2003) categorized information systems in terms of whether they support knowledge creation, storage, transfer, or application. This framing of HITs would classify, for example, EHRs as knowledge-storage devices, decision-support systems in terms of knowledge application, and order-entry systems in terms of knowledge transfer. Although this approach is a step in the right direction in that it focuses on the role that technologies play in the information flow, it too conceptualizes cognition in a static, context-insensitive way by assigning to HITs a single information role and viewing knowledge as a static and explicit resource. Once again, the situated, emergent, and dynamic role that HITs play in EBHC activities is lost.

The upshot here is that HITs cannot be defined and designed independent of the environments in which they are used. The real limits of extant definitions of HITs lie in the way they obscure, rather than highlight, the complex relationship that binds them to their real-life environments (Ash et al., 2009). Conceptualizations of HITs that preclude the possibility of seeing HITs as one part of a whole context miss the mark and will inevitably foster misalignments between HITs and the activities they support. In the next section we delineate a contextually sensitive conceptualization of HITs that can support systematic investigation of the dynamic relationships that bind HITs to the EBHC stakeholders who use them.

## DEVELOPING A JOINT COGNITIVE-SYSTEMS APPROACH TO SUPPORTING EBHC ACTIVITIES WITH HITS

Rather than introducing a definition of HITs as such, our point of departure is to articulate the most fundamental role of HITs, which is to "…maintain, display, or operate upon information in order to serve a representational function" (Norman, 1991, p. 1). This serves as the common context or map to help interested parties assess the effectiveness of HITs and through which more specific aspects of HITs can be investigated. In this regard, the flow of information becomes the mark of a well-functioning HIT. To assess this flow, key questions to pursue include (a) Does the HIT store the right information for the activity? (b) Does it process and analyze the information in ways that support the stakeholder and her activity? (c) Does it represent and display the information appropriately to serve the activities at hand? and (d) Does it provide the right types of interaction to enable the stakeholder to work with the information?

To support EBHC activities, we argue that HITs should be conceptualized not in isolation but as joint cognitive systems (JCSs), a unit of analysis consisting of (a) an HIT and its properties and characteristics; (b) the EBHC stakeholder(s) and their characteristics and needs; and (c) the relationship between the two subsystems from which EBHC tasks and activities emerge. Figure 1 diagrams the components of the JCS. A JCS is the environment or context in which information, HITs, and stakeholders can be understood in light of one another, serving and giving emergence to EBHC activities. In a JCS, the HIT and the stakeholder(s) become coupled in a dynamically coordinated cognitive system, and EBHC activities emerge from the shared pattern of information processing and discourse between them. Within the context of a JCS, HITs go beyond the mere support of stakeholder cognition in that they act as independent participants in the information processing required for EBHC activities. Because of this, a holistic understanding of how to support EBHC activities requires reference to both the HIT(s) and the stakeholder(s) in combination (Ash et al., 2004). Conceptualizing HITs as subsystems or components of a JCS respects the principle that no information-processing device can be defined independent of the

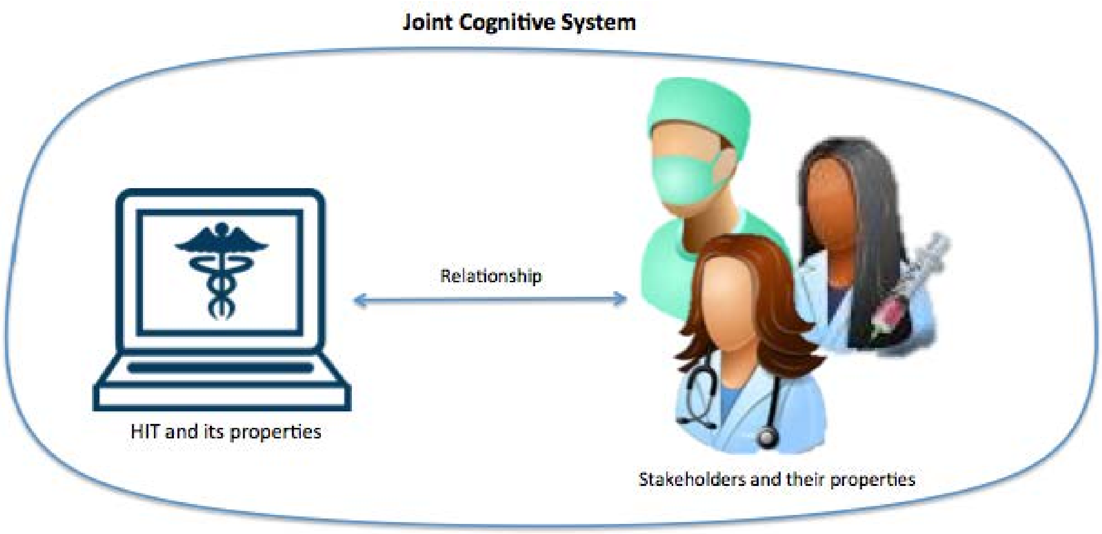


**Figure 1**. The Joint Cognitive System as a unit of analysis includes the health information technology, stakeholders, and the relationship that binds them.

context or purpose it serves. This perspective bypasses rigid and overly abstract definitions that can fetter analysis and dismisses historical assumptions that cognition is isolated within either the HITs or stakeholders themselves.

To understand how to better facilitate information flow within a JCS, the system could be conceived in terms of five subsystems, or spaces, each of which operates upon information in distinct yet interdependent ways. Collectively and in concert, they give emergence to and distribute the load of EBHC activities. The five subsystems are the information space, the computation space, the representation space, the interaction space, and the mental space (Parsons & Sedig, 2013; Sedig & Parsons, 2013; Sedig, Parsons & Babanski, 2012). Figure 2 displays each of these spaces separately, as well as the information processes that occur within them. Decomposing a JCS into subspaces facilitates analysis of the characteristics of the JCS while keeping sight of the whole system that contributes to robust EBHC activities. We discuss these spaces next.

## The Information Space

In the information space, an area of containment serves as the repository of the information used by stakeholders to perform EBHC activities (Sedig & Parsons, 2013). The contents within an information space may be actual or possible, that is, it may already be there or may be generated

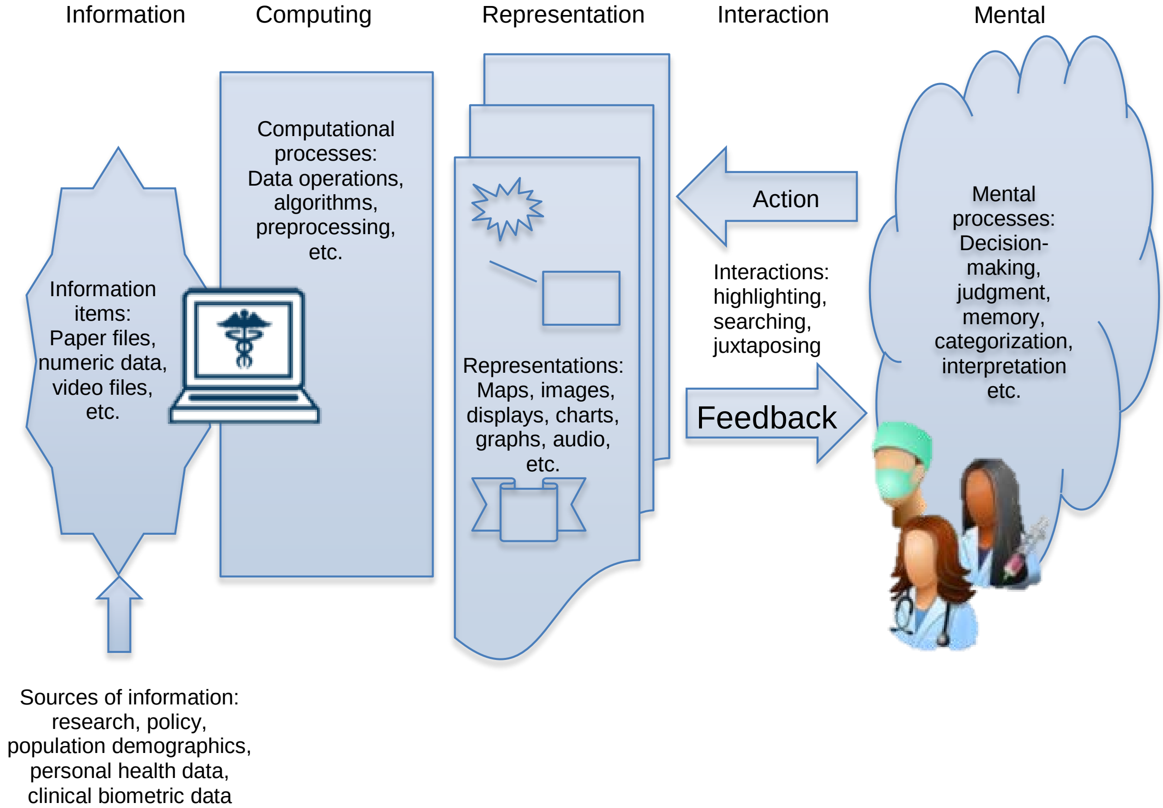


**Figure 2.** The five spaces that comprise a joint cognitive system and the major functions that characterize each space. The first three spaces represent health information technologies, the last reflects the individual capacities in the stakeholder(s), and the fourth encapsulates the interaction between the technologies and the humans.

on an ongoing basis, as in the case of algorithms or other computational processes. Information spaces can combine and maintain information from many different sources or environments within a single repository, allowing the stakeholder (through the mediation of other spaces in the JCS) to utilize them. Within an information space, many diverse types of data or knowledge (e.g., quantitative or qualitative) can be stored at different levels of abstraction, structure, and elaboration. In this sense, data and knowledge within an information space can be complex and multilayered or simple, atomic, and single layered. To illustrate, if a public health analyst requires community information to make better decisions about the advisability of a regional policy implementation, she may consult a geographic information system database and may store data and knowledge from a wide range of types: demographics, health status indicators, community public health resources, cultural information, and/or community narratives. Although information spaces combine and store information within a single repository, this data and knowledge is inaccessible to stakeholders without the mediation of the other spaces, to which we turn below.

### The Computing Space

In the computing space, data from the information space is processed in ways that can render it useful for particular EBHC activities. Although the degree of sophistication of the computational processes depends on the capabilities of the HITs themselves, as well as the needs of the environment, the commonality among the processes within the computing space is that they operate on the data stored within the information space in order to transform it in some way and make it available for EBHC activities. These computational processes can perform functions that range from data cleaning and preprocessing (turning raw data into usable databases) to the computational inferences that have a direct influence on the content of medical decision-making. For example, through text and data mining techniques, HITs can uncover patterns within patient drug response data and integrate them with genomic data to draw pharmacogenetic inferences that might be impossible to make through unaided human cognition. Through subsequent or alternative computational processes, these insights might be made available at the point of care through computational decision procedures, which assist practitioners in targeting drug therapy with the aim of decreasing variability of response. However, data and information will remain latent within the computing space unless made access through representations encoded in the representation space.

### The Representation Space

In the representation space, contents from the information space and processed through the computing space are encoded into forms that are sensible to the stakeholder. Because data and knowledge from the information and computation spaces are never directly accessible to the stakeholder, the representation space plays the crucial role of bridging the gap between them through encoding information into diagrams, maps, images, text, videos, sounds, or other representations (Sedig & Parsons, 2016). A representation is "something that stands for something else" (Zhang, 2002, p. 18) and different representations of the same information can have significantly different cognitive effects (Zhang & Norman, 1994). How well the representations signify the information they encode will depend partly on the purpose for which those representations are intended. No representation will be equally suitable for all purposes, and, because of this, choices about the form and content of representations must be made carefully, bearing in mind the EBHC activities for which the data are intended. For example, global health data can be represented in many different ways (Ola & Sedig, 2016, 2017). The same is true of patient data contained within an EHR, which can be displayed in many different ways (Monroe, Lan, Lee, Plaisant, & Shneiderman, 2013; Rind, 2013; Rind et al., 2011). Among the most common approaches to representing patient information are problem-oriented or source-oriented displays. In problem-oriented displays, clinical data are arranged by the clinical problem, which supports goal-oriented decision-making. On the hand, clinical data in source-oriented displays are arranged according to the location of care, which supports information search and retrieval (Coiera, 2000).

## The Interaction Space

Embedded in the interaction space are all actions and the range of subsequent reactions that are possible within an HIT. As stakeholders act upon the possibilities afforded in the interaction space, subsequent reaction, or feedback, occurs within the representation or computing spaces that allow the stakeholder to dynamically explore, transform, and better use the information within the information space. The interaction (action and reaction) possibilities that exist within a JCS are the foundation for rich, multifaceted, continuous stakeholder discourse with the information, which in turn allows for the discovery of new applications of and perspectives on the information. Some interaction possibilities will serve to support strong discourse between the information and the stakeholder (enabling clear and relevant inferences), while others may confuse, distract, or overwhelm thinking. Interaction possibilities should be encoded into the technology while keeping in mind the context and activity they are intended to support. For example, consider a physician who encounters a patient with a little known genetic condition. If the disease is unknown to the physician, she may search for a diagnosis in a medical research databases by correlating aspects of the clinical case with those detailed in the research findings she collects (Demelo, Parsons, & Sedig, 2017; Parsons et al., 2015). Interaction possibilities encoded into the HIT can allow the physician to highlight various aspects or features of the research findings to check for convergences or divergences between the source and target data. Interaction techniques that allow the patient to filter out extraneous details, hone in on certain aspects of the clinical manifestation, and flexibly group the symptoms together in useful ways will help the thought processes of the physician because they support focus, attention to detail, and concentration (Sedig & Parsons, 2013).

## The Mental Space

Finally, mental space refers to the mind of the stakeholders, which is the location of internal cognitive processes that contribute to emergent EBHC activities. The mental space is what individual stakeholders bring to EBHC activities, as well as the various mental processes required, depending on the content and form that information takes on within the spaces internal to the HIT. Even though the mental space is vital to understanding the role that HITs play in EBHC activities, because we are concerned primarily with HITs, elaboration on the human dimension of this relationship is beyond the scope of this paper.

Taken together, these spaces form the JCS across which information processing is distributed within EBHC activities (Sedig & Parsons, 2013). Because each space contributes an essential presentation, representation, or process in the transformation of raw data and knowledge into usable and appropriately applied outcomes, the spaces do not exist or operate in isolation from one another; each contributes indispensably to the information flow required for EBHC activities. In order to contribute effectively to the unique needs of any particular EBHC activity, each space must be designed to fulfill its specific role and to work in concert with the others, allowing information to flow freely among them for well-defined goals.

At times, the spaces within a JCS may not be designed sufficiently so that they are consonant with one another or with the nature of the EBHC activities being carried out. This can be regarded as a weakly coupled system (see Brey, 2005, for the concept of weak and strong coupling), where the HIT is configured in a way that disrupts, diverts, or undermines the flow of information needed for an EBHC activity. At other times, HITs are well designed to support the needs of the stakeholders and the EBHC activities they carry out. This can be regarded as a strongly coupled system, where the HIT is responsive to its stakeholders' needs, where the information flow is fluid, and the overall experience of getting the information one needs is coherent and satisfying.

JCSs widen the scope of factors to which interested parties can direct their attention when trying to understand how to design and evaluate an HIT in fulfilling its role to support EBHC activities. Furthermore, by analytically foregrounding the relationships that the HIT has with entities outside of itself, the JCS reminds interested parties that HITs are not static or isolated from their environment but are open and permeable systems, giving information to and receiving it from the environment and co-components. In the next section, we direct attention to the relational properties of an HIT that can influence the effectiveness of a JCS in specific EBHC activities. We present the DETECT framework that can assist designers, deployers, and evaluators of HITs to systematically analyze how characteristics of the HIT influence the coupling and healthy information flow within a JCS. As the number of characteristics and factors that affect human-technology relationships are many and these can be presented from different dimensional perspectives, the framework's factors are not intended to be comprehensive or exhaustive; rather, these provide a starting point for analyzing, designing, and evaluating human–technology relationships that serve dynamic EBHC activities.

## DETECT: A FRAMEWORK FOR DESIGNING, DEPLOYING AND EVALUATING HITS FOR EBHC

A framework is a map or structure that helps to identify the elements relevant to a challenge or opportunity and anticipate its systemic outcomes. The spaces of the JCS outlined above have characteristics that influence HIT–stakeholder couplings and the emerging evidence-based activity within a JCS. In this section, we identify characteristics of the four spaces that pertain to an HIT and organize them within the DETECT framework to aid systematic thinking in the context of design, analysis, and implementation of HITs for EBHC activities. The DETECT framework comprises the four levels of factors that correspond with the technological spaces within a JCS (and described more fully above): information, computation, representation, and interaction. Informational factors describe the properties of the data/information used in EBHC activities; computational factors describe the way information processing within the HIT prepares and transforms information; representational factors qualify how information is encoded and displayed in output structures; and interactional factors are those that describe the action possibilities the HIT provides and the reactions from the HIT. We then show how the design, analysis, and implementation of HITs for EBHC can be improved through systematic thinking afforded by the DETECT framework.

## Information

The information space is a repository of the data and materials used by stakeholders to perform EBHC activities. Here we present four characteristics of the information space of a JCS: volume, velocity, variety, and veracity (Chen, Mao, & Liu, 2014).

### Volume

Volume denotes how much information or data is contained within an information space (Hurwitz, Nugent, Halper, & Kaufman, 2013). This can pertain to the number of separate data items, as well as to the number of relationships between and among them. Higher volume information spaces, having more data items and interconnections, tend to require more complex cognition for successful EBHC activities; consequently, these situations can be difficult for unaided human cognition to utilize. For example, a public health professional responsible for a program aimed at preventing cardiovascular disease in a large geographical region will require high volumes of epidemiological and other data, at several levels of aggregation–including demographic and geographical information, public health resources, disease prevalence, risk factors (including tobacco smoking, diabetes, elevated cholesterol, obesity, and low physical activity)–and an inventory of past and ongoing public health policies, programs, and interventions (Howe, et al., 2008; Ola & Sedig, 2014; Sedig et al., 2012). Because high-volume information sources can be onerous or impossible to process by the unaided cognition of health practitioners, other spaces within a JCS can assist by filtering, organizing, or presenting data in ways that facilitate program goals.

### Velocity

Velocity characterizes the rate at which information is processed and may be conceptualized in terms of the throughput and latency of information processing (Sathi, 2012). Throughput may be thought of as the channel capacity or the amount of mobile information that enters and moves through a JCS, while latency is the rate at which that information is transmitted from one component of a JCS to another. A high latency condition suggests a poor transmission level. Both the throughput and latency of an information space can be vital to the success of EBHC activities. Consider, for example, the monitoring and surveillance activities involved in response preparedness to a potential outbreak of infectious diseases. Because traditional surveillance methods, such as routine hospital or laboratory reports, rely on patient visits, they can be slow as a method of collecting information. High latency methods can be supplemented or replaced by lower latency inputs, such as disease-related content crowd sourced from social media or Web engine searches (Brownstein, Freifield & Madoff, 2009). Ultimately such technological solutions can serve to increase the rapidity of public health response to disease spread and mitigate its negative impact.

### Variety

Variety is the diversity of sources from which information enters an information space. High variety information spaces refer to those that draw on several forms of heterogeneous data. Demands for more complex human cognition increase with high variety information spaces because the diversity of information inputs require correlation and extrapolation among sources whose content may bear differently on the relevant EBHC activities. Take, for example, the variety of forms of data that physicians use in making decisions at the point of clinical care: unstructured medical histories and notes; laboratory test results; hospital admission and discharge records; medication records; MRI, CT and other images; and email or voice message communications from other providers in the clinical team (Raghupathi & Raghupathi, 2014). The tremendous variety inherent in the information used by clinicians at the point of care demands cognitive work to integrate, synthesize, and streamline into a coherent decision. Hence information characterized by high variety should be used to support cognitive activities where synthesis and integration needs are not time-sensitive or pressing.

### Veracity

Veracity refers to the assurance that information within an information space is error free (Sathi, 2012). Information spaces may exhibit low veracity when the origins of their inputs are unknown or the data processes on which they rely are unreliable, noisy, or imprecise. For example, program planning in public health that draws on data mined from social media generally exhibits lower veracity than data drawn from more traditional formal techniques, such as experts or routine surveys (Herland, Khoshgoftaar & Wald, 2014). When brought to bear on a particular point of interest in public health planning, social media data can be inflated, exaggerated, or biased by external factors; they may betray a high noise-to-signal ratio; or such information may incorporate a set of premises that render them irrelevant and misleading. By contrast, data from routine surveys that are preformatted to address well-defined public health planning issues and administered to qualified respondents present inherently more reliable and precise information. Because of the added processing associated with compensating for low veracity information spaces, EBHC stakeholders may have a difficult time deriving clear conclusions from them.

## Computation

A computing space is where a set of computing models and algorithms operate on information. Six properties of the computation space are reasoning, complexity, input, noise, autonomy, and temporality.

### Reasoning

Every computation space employs various reasoning techniques or genres, such as clustering algorithms (e.g., k-means or density-based spatial clustering of applications with noise) or rule-based models (e.g., decision trees), among others (Silva & Zhao, 2016). Variations in the reasoning capabilities of the computation space can radically change the kind of support offered by an HIT. For example, some health informatics tools function by tapping the collective EHR knowledge of the thousands of providers that utilize them within a country and/or internationally. Thus, when a dermatologist encounters a rare skin disease that reveals an immediate gap in her knowledge, a computation space with clustering capabilities can enable her to access the knowledge from other providers about similar patient visits. When the computation space has the algorithmic capacity to dynamically cluster together patients with similar medical profiles or clinically similar situations, the care provided by the dermatologist can be better informed, more relevant, and more effective.

### Complexity

The multifaceted property of complexity refers to the degree of inherent difficulty within the problem or tasks that the computation space can solve, as well as the structural (i.e., number of algorithmic components and their interrelatedness), temporal (i.e., amount of time), and spatial (i.e., storage and computational components) resources that are needed to deal with such problems or tasks. Computation spaces that exhibit a high degree of complexity are able to handle stakeholder tasks that involve high degrees of computation, time, or storage capacity and the rising complexity of HITs open new horizons for clinical practice. For example, advances in computational complexity have recently given rise to the possibility of assembling and sequencing billions of DNA fragments that compose the human genome. These, in turn, give rise to the possibility for personalized medicine, which seeks to tailor preventative or therapeutic interventions to specific groups or individuals. Computation spaces that exhibit a high complexity can assist stakeholders in undertaking EBHC activities that would be impossible with human cognition alone.

### Input

Input refers to the data types that the computation space can handle. For instance, some algorithmic models require labeled data (e.g., support vector machines and decision trees need data points with a categorical attribute known as the class attribute or the dependent attribute). Others can work with unlabeled data (e.g., k-Means needs no class attribute in the data), while others may need a specific dependency in the data (e.g., time series data; Silva & Zhao, 2016). For example, deciding the plan of care for a terminally ill intensive care patient may involve reasoning with several inputs of different types, including biometric data, test results, patient preferences and directives, clinical narratives, and chart notes on the patient's history. Depending on the condition and preferences of the patient, the way the attending physician integrates these different types of information can radically alter the framing of and approach to care. A computation space that has the capacity to utilize diverse data types in decision support can be a powerful aid to the physician and improve the quality of treatment offered.

### Noise

Computing spaces vary in the degree of tolerance in handling noise, error, and/or unknown attribute values in the data. Noisy data may have spurious omissions or additions, be characterized by systematic measurement errors, affected by the context or background, or compromised in some other way. Some computation spaces are sufficiently equipped to effectively assist EBHC activities through more and better utilized data. For example, a chief public health officer can better understand the factors causing domestic violence in a region by relying on the data collected through the region's hospital system. Using this data, which is often characterized by noise and spurious inputs, will only be possible if the computation space is capable of performing operations upon and deriving value from noisy data.

### Autonomy

The degree to which a computation space can act without stakeholder supervision, steering, input, and/or oversight represents its autonomy. While having fully autonomous computing systems is challenging, computation spaces can require varying degrees of human intervention in their operation. For instance, in the case of machine learning, which is becoming an integral part of today's health informatics tools, algorithms may be supervised (e.g., support vector machines and regression), requiring humans to train algorithms with given data to produce viable models; semisupervised (e.g., active learning), requiring less human intervention than the supervised ones; or unsupervised (e.g., k-means), requiring no humans to train algorithms (Fang et al., 2016; Rubens, Elahi, Sugiyama, & Kaplan, 2016; Silva & Zhao, 2016). Naturally, specific types of EBHC activities will benefit from different levels of computational autonomy. Consider two cases requiring different degrees of computational autonomy: detecting brain tumors versus assessing risk of readmission of congestive heart failure patients. The first case involves analysis of brain images and CT scans. For this, a supervised support vector machine algorithm can be used to classify whether or not a patient has tumor. The second case requires a clustering of different patients. For this an unsupervised k-means machine learning algorithm can be used to partition the space of different patients.

### Temporality

The degree to which the computation space can handle time-based data and, if so, how often (i.e., at what time intervals) it can receive incoming data defines the temporality of the space. A computation space can work on existing datasets, accept new data at regularly scheduled time points, or deal with instantaneous real-time data. For instance, in a computer-assisted surgical procedure for prostate cancer, the surgeon relies on visualizations and other biometric data current to the second. By contrast, during public health surveillance efforts, the temporality of the computation space can be less frequent, sampling data every day or two. Achieving the right temporality of data sampling is an important characteristic of a properly tailored computation space to the EBHC activities, as is achieving a strong coupling between the HIT and the stakeholder.

## Representation

In the representation space, contents of the information space are encoded into representations and made visible to the user. We identify five characteristics of representations that can be manipulated to support a strong coupling within a JCS: complexity, interiority, configuration, type, and density (Parsons & Sedig, 2014).

### Complexity

Complexity refers to the degree to which the representations displayed in an HIT are detailed in the number of items, encoded properties, and relationships. Complexity can range in value from low (e.g., a single item with no presented relationships) to high (many items within an elaborate network of relations in the representation space—i.e., the display). When the complexity of representations in an HIT is not commensurate with the EBHC activities for which they are used, human cognitive overload and errors may result (Norman, 2013). Representations that are too simplistic cannot store or display the information necessary for complex tasks, while representations that are too complex can overly tax the perception, attention, working memory, or other cognitive processes of the stakeholder. For example, consider a psychiatrist working on the medication regime of a patient. The task in this case will depend on whether the psychiatrist is devising the drug regime for the first time or merely updating a routine drug regime. In the former case, when the psychiatrist is devising the drug regime from scratch, a more complex representation highlighting many aspects of the problem will help advance the activity smoothly. For instance, patient characteristics, potential drugs to prescribe—including their respective mode, frequency and time of intake, and dosage options—and whether the drugs are name brand or generic may all be immediately relevant. In the case where the psychiatrist is merely updating an already formulated plan, too many irrelevant or redundant details may interfere with the progress of the task, which largely consists of verifying preset measures.

### Interiority

Interiority is the degree to which unencoded data items lie latent within the representations, not explicitly encoded, while still being potentially accessible. Values in interiority range from low, such as when all the information is encoded into the representation and accessible on the immediate level to the stakeholder, to high, where most of the information resides below the surface of a representation, yet to be encoded explicitly. A balance must be struck in how much information to encode for a particular task: Too much extraneous information in a representational scheme can be distracting, while too little will force stakeholders to fill in the gap themselves, or seek the information elsewhere. For example, the main menu of hospital EHR systems often provides a balance between the horizontally (which encodes information at the same level) and vertically nested (which embeds information within superordinate classifications) structures. When a practitioner requires more than summary details of the plan of care being executed, she will need to drill down into the vertically nested categories to retrieve the desired details. The way and extent to which information is interiorized can have a significant effect on the speed of access, as well as the interpretive processes of the practitioner.

### Configuration

Configuration concerns the principles behind the ordering and arrangement of the information items in the representation space of an HIT. Encoded information can be configured through a number of approaches, including by attributes of the information (e.g., nominal, ordinal, cardinal), perceptual characteristics of the representations (e.g., size, color, font, formatting), or by some principle specified by the designer (e.g., alphabetical vs. chronological). Variations in the representational configurations of an HIT can have a pronounced influence on EBHC activities, obscuring some attributes of the information and highlighting others. For example, in a comprehensive drug information resource, arranging the drugs by their alphabetic name can aid searchability, while obscuring information about potential side effects, possible drug interactions, or the precautions the patient must take in using the drug that could be more visible in a different categorization strategy. In many cases, allowing the stakeholders to control the configuration of the information can assist them to detect easily any patterns, trends, or relationships in the data, bypass irrelevant information, or reorder data to fit a specific activity or need.

### Type

The forms in which information is encoded—which may include, among others, plots, charts, images, diagrams, symbols, and text—reflect the type. Different types of representations offer various drawbacks and benefits in use by stakeholders (Larkin & Simon, 1987; Parsons & Sedig, 2014). For example, in reasoning about the influence of long-term eating behavior on chronic illness, charts and diagrams encoding this data can assist medical researchers to identify patterns and discontinuities at a glance and to visually compare different data sets to easily draw insights or conclusions. Although some types of representations, such as charts, plots, and diagrams, help researchers to understand continuous data, other discrete representations, such as symbols or text, are better for precise, detail-oriented EBHC activities. Furthermore, being able to transform one type of representation to another can facilitate the performance of EBHC activities.

### Density

Density is a measure of how much information is within a given representation space. Diffuse representations take much space to encode and communicate little, while dense representations express their information compactly. However, if a representation is too dense, it requires a high degree of accuracy and precision and, as a result, can encourage errors. Meanwhile, diffuse representations can undermine the efficiency and speed of EBHC tasks. For example, EHRs used for inpatient care often have to communicate several types of complex, layered, and interrelated information at the push of a button: administrative and billing data, patient demographic and history, progress notes, vital signs, diagnoses, medication lists, and radiological images. If the representational scheme used to assist stakeholders in locating and interpreting the information contained therein is too dense, the stakeholders' attention can become overwhelmed or miss some representations. Density should be used according to the needs of the EBHC activity as well as the experience of the EBHC stakeholders.

## Interaction

The interaction space contains all the action and reaction possibilities that are available to the user. We identify five aspects of the interaction space that can be manipulated to strengthen the couplings within a JCS: visibility, flexibility, diversity, complementarity, and directness (Sedig et al., 2012).

### Visibility

Visibility concerns the extent to which an HIT makes its interaction possibilities and behavior perceptible to the stakeholder. This includes awareness of the interaction possibilities that an HIT supports, as well as the encoding of a perceptible response when an action or reaction takes place. When interaction possibilities and the actions and reactions that are carried out with them are explicit, stakeholders will often have an easier time using the HIT and will be able to keep better track of the effect of their actions on the HIT. Keeping track of one's actions and their effects is a core task in using HITs effectively. For example, Nemeth and colleagues (2005) studied the use of infusion pumps by stakeholders in medication delivery and concluded that interfaces should provide more explicit information about their past, present, and future states. They found that the substantial programming required, and the array of layered and nested menus with complex branching options, served to confound even the most experienced operators. Stakeholders using the infusion pumps frequently became confused, had difficulty tracking their state of operation, and had to work through several misinterpretations before correctly setting the device. Most clinicians developed coping strategies that were effective but vulnerable to failure. Allowing more conscious control over the visibility of certain interaction possibilities and the state and consequences of interactions can assist stakeholders in better interpreting the HIT, thus laying the foundation for stronger, more coherent relationships within the JCS.

### Flexibility

The availability and range of adjustability options that allow stakeholders to manipulate the values of several characteristics of the HIT to suit their needs, circumstances, or goals reflects a technology's flexibility. For example, an HIT that allows the stakeholder to adjust the visibility of its interaction possibilities, rendering some invisible and others visible, is more flexible than one that does not. Highly flexible HITs can allow the stakeholders to adjust a range of characteristics, from those dealing with information, computation, and representation to the interaction possibilities themselves. To further illustrate, consider an HIT that provides decision support to stakeholders in the form of computerized alerts and reference information. Depending on the stakeholders, the work environment, and other contextual factors, it may be useful to manipulate some of the features of the decision support, including the onset, frequency, detail, kinds of information offered, or level of inference carried out by the HIT. Although highly flexible HITs can prove very helpful in some cases, flexibility can sometimes place tremendous responsibility on the stakeholders, requiring them to think through and consciously adjust factors for which they may have little preference. Therefore, at times, rigid structure and predictability are preferable, especially when the EBHC activity is linear or unambiguous.

### Diversity

Diversity concerns the number and range of interaction possibilities available to stakeholders. Different forms of interaction will enable stakeholders to gain diverse perspectives on the information and to apply it in multiple ways. Therefore, a high diversity in interaction possibilities can assist stakeholders in their ability to perform autonomous, well-rounded EBHC activities. For example, when a pharmacist seeks to update a patient's drug regime, she will need to investigate, among other things, the relationship between an indicated drug and any potential drug interactions with the patient's existing medications. Diversity in interaction possibilities in an HIT can help the pharmacist perform a range of operations to understand the drug interactions more holistically. An interaction that allows the pharmacist to place drug properties side by side can highlight common properties and side effects, while another interaction that allows the pharmacist to investigate several drugs in terms of a single property can portray the drugs as a common set, highlighting different characteristics. Further, an interaction that allows the pharmacist to translate the form of information presentation from linguistic to animated display to show the mechanism of action can illustrate clearly information that is difficult to grasp with text alone. In this way, diverse interaction possibilities can serve diverse cognitive needs of EBHC activities. Still, too much diversity can be counterproductive. As a rule, HITs should offer a number and range of interactions that are commensurate with the needs of the EBHC activities and the external environment, offering no more nor less variety than is needed for the complexity of the tasks it is used for (see law of requisite variety, Weick, 1979).

### Complementarity

The harmony of relationships among interaction possibilities, and how well they work with and supplement each other, forms the complementarity of an HIT. A high degree of complementarity among the interactions allows stakeholders to conduct more coordinated and integrated EBHC activities. That is, although each individual interaction independently supports only one particular action, collectively the interactions can work together and assist stakeholders perform more complicated EBHC activities. Consider the case of a psychiatrist formulating a differential diagnosis and possible etiologies for a patient with a decreased level of consciousness. In using an EHR system to assess differential diagnoses (e.g., street drugs, vitamin deficiency, meningitis), the interaction possibilities may be embodied in such a way as to force the psychiatrist to carry these steps out in a linear and overly restrictive fashion. HITs that respect the organic and interconnected nature of the diagnostic process will make provisions for how different steps of the diagnostic procedure rely upon and influence one another.

### Directness

Directness addresses the degree of straightforwardness toward a desired goal or task that is encompassed in the interactions within an HIT. Interactions that are direct allow stakeholders to act on and receive feedback from the desired information without an intermediary, while HITs with indirect interactions have the stakeholders operate upon secondary or ancillary information sources in order to access their object. Direct interactions also allow stakeholders to carry out

EBHC activities parsimoniously, that is, with the fewest number of steps possible. For example, when a community nurse practitioner attempts to understand the seriousness of a patient's symptoms (e.g., abdominal distension and blackened stool), a medical reference database can either allow her to organize information directly through the agency of the symptom of interest or only through the mediation of some other medical category. In the former case, the nurse practitioner can directly form a coherent sense of the seriousness of the symptoms, their potential ramifications, parallel symptoms or conditions to watch for, and which tests may be relevant or irrelevant. In the latter case, however, indirect interaction possibilities force the nurse practitioner to extend and extrapolate her inferences through a source of indirect interest, thus multiplying the number of steps required to access the desired information.

To summarize, the DETECT framework offers 20 factors that designers, deployers, and evaluators of HITs can use to characterize the fit between HITs and the EBHC activities they serve. Each of these factors can be modulated by other factors depending on the type of EBHC activity, the intended user group, or other aspects of the environment. In Table 1, we give an overview and visual summary of the whole framework.

## SCENARIOS

This section demonstrates how the DETECT framework can assist designers, deployers, and evaluators to better align HITs with dynamic, real-life EBHC activities. In this section, we illustrate the kind of systematic analysis that DETECT facilitates and the way it can support diagnosis of problems in the design and use of HITs if and when they arise. We outline two scenarios, each illustrating a different pole on the spectrum of cognitive work (Nemeth et al., 2005).

### Scenario 1: Public Health Manager Organizing a Substance Abuse Prevention Program

Our first scenario explores the utility of HITs at health-care's blunt end (which includes health management, public health planning, and policy), where EBHC activities are typically more diffuse, broader, and contemplative, rather than fast paced and highly dynamic. Consider a public health manager deciding whether to fund a particular substance abuse prevention program for a midsized city. The main question she is assessing in making this decision is whether there is reason to believe that this program will actually prevent substance abuse in her city. To answer this question, she identifies and assesses research evidence, evaluations of the program from other cities and localities, and local community feedback that are presented in a public health research HIT. Specifically, she is interested in collating and summarizing the criteria to be used to evaluate the efficacy of the program and in applying these criteria to the needs of her city.

In her HIT, the public health manager is reviewing several dozen empirical studies, a few government reports, privately conducted program evaluations, and one community workshop's feedback compiled into a YouTube video (all imported into the HIT on a previous occasion). Because she finds several evaluation criteria in the resources, the public health manager's task in comparing these criteria becomes more complex and subjective. To better understand and synthesize the results, she sifts through the resources to identify and list all the indicators used

**Table 1.** Properties of HITs Useful in Analyzing Their Alignment with EBHC Activities.

| Space | Property | Characterization |
|---|---|---|
| Information | Volume | How much data is contained within an information space |
| | Velocity | The rate at which data is processed within an information space |
| | Variety | The diversity of sources from which information enters an information space |
| | Veracity | The assurance that information within an information space is error-free |
| Computation | Reasoning | The reasoning techniques employed by the computation space |
| | Complexity | The level of difficulty of problems that the computation space can solve |
| | Input | The types of data that the computation space can utilize |
| | Noise | The computation space's degree of tolerance to error or unknown attributes in the data |
| | Autonomy | The degree to which a computation space can act without stakeholder supervision, steering, input, and/or oversight |
| | Temporality | Whether the computation space can handle time-based data, and how often it should receive incoming time data |
| Representation | Complexity | The degree to which representations are detailed in the number of items, properties, and relationships they encode |
| | Interiority | The degree to which unencoded data items lie below the surface of the representations |
| | Configuration | The ordering, arrangement, and organization of information items in the representation space |
| | Type | The forms in which information is encoded (e.g., plots, charts, images, diagrams, symbols, text) |
| | Density | How much information is within a given representation |
| Interaction | Visibility | The extent to which an HIT makes its interaction possibilities perceptible to the stakeholder |
| | Flexibility | The availability and range of options allowed the stakeholder to adjust the characteristics of the HIT |
| | Diversity | The number and range of interaction possibilities that are available to the stakeholder |
| | Complementarity | The degree of harmony of relationships among interaction possibilities |
| | Directness | The degree of straightforwardness of the interactions toward a desired goal or task |

to measure program success. Some studies measure efficacy in terms of reduction in substance abuse; others focus on cost evaluation, community satisfaction, or other indirect social outcomes measures (e.g., rates of absenteeism in the community or family violence). The public health manager identifies and compiles the results of the available evaluation criteria to see what conclusions she can draw about the program's efficacy elsewhere. Beyond this, she weighs the conclusions presented in each study in light of the strength of that particular research methodology: the study design, reliability of the measures, and the strength of the effect. The HIT allows the public health manager to access and display the resources, but it also has some functionality to assist her in comparing the resources along key points of interest. Taken together, the research HIT and public health manager form the JCS that carries out the EBHC activity needed to answer her question. For the benefit of our research aims, examining how each of the constituent spaces of Scenario 1's JCS contributes to the activity will help us assess how these spaces work together to achieve the EBHC activity goal.

The information space in this case exhibits a high volume of information. It also contains a high degree of variety, with surfaced studies containing narrative, qualitative, and statistical evaluation criteria. The data in the studies concern issues as diverse as the rates of substance abuse, which substances are abused, the possible causes of substance abuse, the effect that the substance abuse prevention program had on a range of factors, and the influence of some confounding variables. Because the studies dealing with this particular substance abuse program are few in number, the velocity of the information space is low; however, the veracity is high because the sources provide primarily peer-reviewed information.

To assist the public health manager digest the relevant information, a computation space is designed with the characteristics of the information space in mind. The computation space should be equipped to process diverse data input types, that is, to integrate video, numerical, and text formats. If program evaluation criteria can automatically be culled from different sources, this will assist significantly the manager's decision making. Although a high degree of inputs are needed, the computation space need only possess a low degree of noise tolerance because the data is relatively clean. Additionally, a low complexity of operations on the data will likely suffice the manager's needs. That is, because the public health manager is looking for summaries of existing studies, the HIT will only need to provide simple correlations, trends, or summaries of the information. Because the decision on a program is not fully formalized (i.e., the decision still involves subjective elements), the process of deciding whether to fund this public health initiative will benefit from a computation space that carries out activities in close collaboration with the demands of the public health manager, rather than an autonomous or independent computational space; hence, a low degree of autonomy is desirable. Figure 3 shows each factor of the DETECT framework for this case and categorizes it as high or low.

Because the information in the studies is multilayered and multidimensional, the public health manager can benefit from representations with a high degree of complexity and interiority. Public health interventions are notoriously complex (Rychetnik, Frommer, Hawe, & Shiell, 2002), involving many confounding factors that can increase the manager's cognitive load and distract her attention. A complex representation that encodes these extraneous variables can preserve the rich interconnections characteristic of social health data and encourage holistic and rigorous evaluation. In the same way, representations with a high degree of interiority can assist the public health manager in pacing herself by externalizing aspects of the information only when demanded. This can facilitate a measured, yet in-depth, conversation with the information, allowing the manager to look at multiple aspects of the evaluation criteria she has collected. In turn, such components of the representation space can assist the public health manager in avoiding potential biases in causal reasoning that may attend thinking about complex phenomena (Sterman, 2006). Furthermore, a representation space with a flexible configuration will help aid the public health manager in exploring many facets of the information by arranging it in different ways.

| Space | Degree | Characterization |
|---|---|---|
| Information Space | ↑ | Volume |
| | ↑ | Variety |
| | ↓ | Velocity |
| | ↑ | Veracity |
| Computation Space | ↑ | Input |
| | ↓ | Noise |
| | ↓ | Complexity |
| | ↓ | Autonomy |
| Representation Space | ↑ | Complexity |
| | ↑ | Interiority |
| | ↑ | Configuration |
| Interaction Space | ↑ | Diversity |
| | ↑ | Visibility |
| | ↓ | Flexibility |

**Figure 3**. Example of a JCS characterization that supports public health cognitive activity

The nature of the information used in this case analysis is social and complex, rather than linear and formulaic. Thus, the public health manager will most likely independently analyze each criterion used to measure program success, as well as how the program fared when considered along those criteria. Although the criteria are clear, they are numerous and distinct. Hence, to assess the program, the manager would most likely prefer to be able to witness her own operations on the data as she formulates her questions, draws inferences, and settles on conclusions. This will allow her to keep better track of her conclusions as she makes judgments relating each criterion to the wider scope of her purpose. Furthermore, because the information is multifaceted, the manager will benefit from having available a wide degree of diversity in the interaction possibilities available to her. For example, allowing the manager to measure the program efficacy by program cost will help her draw conclusions about its feasibility for and benefit to her own city. Relatedly, perhaps she may benefit from comparing the efficacy of the program in relation to the characteristics of the populations involved in the research.

As articulated in this scenario, both the HIT and the public health manager contribute to the ultimate decision on funding the campaign. As illustrated, using the DETECT framework to systematically guide decisions about the utility of technological parameters in light of the needs of the user and activity can help create more robust EBHC activities. A well-coupled JCS can assist the public health manager draw well-informed and workable conclusions from the rich and multifaceted information in the HIT. On the other hand, an HIT that is not suited to the needs of the manager can obscure the information and hinder the emergence of holistic and rigorous conclusions.

### Scenario 2: Psychiatrist Ordering Drugs through a Computer Order Entry System

Our second scenario illustrates the utility of HITs at health-care's sharp end where EBHC activities are more specific, direct, denser, and faster (including medical, nursing, and the pharmaceutical care). Because EBHC environments at health-care's sharp end tend to be more responsive (where the consequences of actions accrue more quickly) and more interdependent (where inputs display more interdependence), the activities carried out in these environments tend to be more sensitive to error and require higher reliability (Nemeth et al., 2005; Weick & Sutcliffe, 2011).

Consider in this instance an inpatient psychiatrist ordering drugs for a newly admitted patient with a bipolar disorder. To design the drug regime, the psychiatrist needs to match any drug to the patient's symptoms; adjust for comorbidities, contingencies, or interactions; and set the administration parameters (i.e., drug type, dose, mode of delivery, onset, duration, and frequency). Figure 4 shows an example of a joint cognitive system that supports a medical cognitive activity.

In ordering drugs for the patient, the psychiatrist typically utilizes the computer order entry (CPOE) system in the ward. The information space that will support this activity is characterized by a low volume. The HIT contains a number of preset drug parameter options (i.e., drug, dosage, frequency, onset, duration, form), patient-specific information about allergies and her current medication regime, and a list of preprogrammed drug incompatibilities. With a tentative drug regime in hand, the psychiatrist uses the drug administration parameters available in the HIT to better formulate an administration plan, seek feedback about the proposed drug regime, and resolve any allergy or interaction problems that the system flags. Because the information in the HIT concerns drug parameters and interactions, the information space is characterized by low variety, and because the data are revised and refreshed several times daily, or upon request, the velocity is relatively high.

To assist the psychiatrist in the activity, the computation space performs certain subtasks of the activity that save time and the psychiatrist's attention. When drug interactions are identified, the HIT can assist the psychiatrist by suggesting alternative drugs with similar profiles and, as a result, this HIT requires a high degree of reasoning. Despite this, the HIT need not be characterized by a high degree of complexity because checking the potential interactions between drugs is defined by a clear method and desired outcome. To support the psychiatrist in keeping track of administration details in an exact way, the HIT can be characterized by a low degree of noise tolerance. Lastly, because the required cognitive processes in order entry

| Space | Degree | Characterization |
|---|---|---|
| Information Space | ↓ | Volume |
| | ↓ | Variety |
| | ↑ | Velocity |
| | ↑ | Veracity |
| Computation Space | ↑ | Reasoning |
| | ↓ | Complexity |
| | ↓ | Noise |
| | ↑ | Autonomy |
| Representation Space | ↓ | Complexity |
| | ↑ | Configuration |
| | ↑ | Density |
| Interaction Space | ↑ | Directness |
| | ↓ | Visibility |
| | ↓ | Flexibility |

**Figure 4.** Example of a JCS characterization that supports medical cognitive activity.

are narrow and clear, a high degree of autonomy is warranted in the HIT. That is, the HIT should complete whole processes without requiring steering by the psychiatrist because too much required interaction between the psychiatrist and system would interfere with clinical workflow.

In the representation space, representations helpful in serving a robust order entry process will encode information with a low degree of complexity and an approach to configuration that highlights useful dimensions of the information. Firstly, an HIT interface with a high degree of complexity can serve to derail the drug ordering process by introducing unnecessary concepts and ideas into what should be a well-delineated, detail-oriented process. As a rule, unnecessary details (e.g., drug history, generic vs. name brand) should not be encoded explicitly at the level of the representations but should be resolved by placing information below the surface of the representation, to be summoned on demand, or by arranging such decisions beforehand.

Secondly, administration-relevant information can be communicated visually in a well-designed configuration. For example, dosages can be calculated according to patient weight through representations that use relative size; the degree of risk associated with drug interactions through color; and the titration of drugs according to standard dilution ratios can be facilitated through use of position and location. Thirdly, because drug information is a form of explicit knowledge—received through training and education—representations that are very dense often can be learned easily and serve to make the process efficient without confusing the practitioner or endangering patient safety.

Lastly, in the psychiatrist's ability to interact with the HIT, one should expect a high degree of directness, relatively low flexibility, and low visibility. Again, because the process of order entry is a restricted activity rather than open-ended, the HIT's interaction possibilities should constrain and guide the psychiatrist towards her prespecified end. For example, if the psychiatrist seeks to order a dose of lithium for bipolar disorder, she is best served when the HIT guides the activity along closed channels that meet the guidelines of safe order entry practices (rather than, for example, assisting the psychiatrist explore the many pros and cons of lithium). Supporting the same goal, one can expect that the visibility of interactions be low, thus making outcomes of interactions (e.g., errors, omissions, or ambiguities) visible while keeping the process-oriented interactions invisible to the psychiatrist. Lastly, because of the constrained, prescriptive nature of order entry, one might expect that the flexibility of the interaction possibilities to be minimal in that a high degree of freedom in adjusting the parameters of order entry can undermine the streamlined nature of the activity.

This case shows how the evidence-based decision of creating a medication regime is the product of both the psychiatrist and HIT working together. Thinking of these two partners as a JCS and analyzing the dimensions of their relationship helps explain whether and how they can work together well. A strong coupling between the psychiatrist and HIT can assist the psychiatrist in focusing on the important aspects of her job (e.g., reasoning about the manifold consequences of the proposed drug regime, and planning contingencies), rather than getting caught in the details of administration.

## IMPLICATIONS FOR RESEARCH AND APPLICATION

In this paper, we provide designers, deployers, and/or evaluators of HITs with a coherent framework with which to identify the factors that mediate the relationships between HITs and their environments. In using the DETECT framework, interested parties will be able to better identify, describe, and adjust the relationships between HITs and the stakeholders performing EBHC activities. By foregrounding relationships and analyzing them systematically, we believe that our approach can assist practitioners avoid the linearity that is characteristic of previous approaches and, as a result, take a step toward the goals of reducing the misalignment gaps that currently exit between HITs and EBHC activities. This can in turn improve the adoption rates of such technologies, maximize their utility, and minimize the errors that are documented across the EBHC literature.

The DETECT framework is not intended to be a faithful description of reality but rather a conceptual toolkit that can help with how HITs that permeate the world of health care should be conceptualized, described, analyzed, designed, and evaluated. We argue that based on the HIT literature that has yet to present any framework of factors that would allow the achievement of such a coherent set of considerations, this initial attempt can open a new line of research and theorizing, ultimately leading to useful and usable HITs for EBHC activities. The value of the DETECT framework lies foremost in allowing interested parties to operate in a manner that is holistic in attention to the range of factors at play and in the systematic modulating of those factors to ensure a better fit between HITs and EBHC activities. Finally, we advocate a closer rapprochement between EBHC activities and the HITs that are weaving themselves into the medical field's daily fabric.

## CONCLUSIONS

The DETECT framework is a step towards a better fit between HITs and the EBHC activities they serve. Yet, DETECT has some limitations. Firstly, a more comprehensive approach would have to take into account literature from health informatics, health information, and health-care knowledge management. But, such an approach would make any single paper or research project unwieldy. So ongoing research employing multiple sources, fields, and methods is advocated. Secondly, it may well be that other researchers could conceptualize a wider diversity of spaces or more characteristics of those spaces. However, in order to concisely describe the framework and some of its immediate applications and leave room for its future expansion, we chose to let any wider conceptualization to lie beyond the scope of the current paper. However, the EBHC and HIT research communities can benefit from what is presented as a launching point for broader and deeper exploration of the concept of using a JCS approach to design and implementation of HITs for successful EBHC activities.

## ENDNOTE

1. For simplicity, all third-person singular pronouns are presented in a single form (feminine) but are intended to be gender inclusive.

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