

Cognitive Informatics in Biomedicine and Healthcare

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1 Introduction: Role of Cognition in Biomedical Informatics

We are at a turbulent, yet exciting, phase in healthcare – *turbulent*, as the transformations in healthcare practice have been driven by paradigmatic shift towards the use of health information technology (HIT), both as a result of necessity and federal mandates; *exciting*, as such transformations have highlighted the central role of cognitive and behavioral sciences in developing usable systems that can provide high quality patient care. While there is a bright future, in terms of opportunities for researchers and practitioners who seek to engage in cognitive science research, it is also important to *reflect on past research* – to understand (a) the historical context and foundations of the development of cognitive research in biomedical informatics, (b) the theories, constructs and frameworks that drive the current research; and (c) the potential directions for future research. Within this focus, this special communication provides a broader context of the cognitive and behavioral research on HIT in biomedical informatics. In addition, we have also created a *virtual issue* of the *Journal of Biomedical Informatics* (JBI) that will provide a snapshot of the research that has been published in JBI pertaining to cognitive and social science research (See references, [1-57]).

Cognitive science is an interdisciplinary field that draws from psychology, computer science, linguistics, philosophy and anthropology to understand human activities including reasoning, decision-making and problem solving. Principles from cognitive science have been applied for studying the usability of medical devices and interfaces [55]; developing training, educational interventions and guidelines [39]; streamlining and improving workflow and clinical processes [29]; and for understanding the process of clinical judgment, reasoning and decision-making [58]. In summary, cognitive science provides a viable mechanism to inform our understanding in technology-rich clinical environments, and represents an important component of biomedical informatics [59]. Additionally, cognitive research has been a key to shaping and structuring the use of HIT, adapting to the various needs of the clinical environment.

Cognitive Informatics (CI), by extension, is an interdisciplinary field comprising of cognitive and information sciences, specifically focusing on human information processing, mechanisms and processes within the context of computing and computer applications [60, 61]. The focus of CI is on understanding work processes and activities within the context of human cognition and the design of interventional solutions (often engineering, computing and information technology

solutions) that can improve human activities. Within the context of biomedical informatics, CI plays a key role – both in terms of understanding, describing and predicting the nature of clinical work activities of its participants (e.g., clinicians, patients, and lay public) and in terms of developing engineering and computing solutions that can improve clinical practice (e.g., a new decision-support system), patient engagement (e.g., a tool to remind patients of their medication schedule), and public health interventions (e.g., a mobile application to track the spread of an epidemic).

Theoretical and methodological approaches from cognitive science have informed the design and evaluation of HIT, and also in understanding and improving the efficiency of healthcare providers. Original research in CI has drawn significantly from cognitive science topics related to comprehension, problem solving and decision. Cognitive research evolved from Newell and Simon's [62] conceptualizations of individual "thought" and "mental processes", and "human problem solving." Original studies of problem solving introduced protocol-analytic approaches [63], human information processing theories that, consequently, laid the foundation for the discipline of human computer interaction (HCI). Methods such as verbal think-aloud have been extensively used in CI research, and have been influential in developing our understanding regarding medical problem solving and decision-making and reasoning. Similarly, Walter Kintsch's [64] research on text comprehension has been instrumental in shaping CI research related to reasoning and decision-making in healthcare.

Recognition of the role of cognition in biomedical informatics has shown slow, but positive, growth. While the role of cognition in characterizing the nature of clinical decision-making, judgment and reasoning has been well acknowledged [65, 66], the prevalence of cognitive science research in mainstream informatics literature did not occur until the late 1990s. One of the key contributions towards the integration of cognitive science and biomedicine came in 1989 with a book that assembled key papers in biomedicine from the fields of cognitive psychology, linguistics, computer science, anthropology and philosophy [67]. The book provided an early scientific foundation of cognition science for investigations in biomedical modeling.

"Cognitive science" as a category of submission at the flagship American informatics conference, AMIA, did not occur until 1996. Internationally, such interest developed a few years later (with recognition at, for example, the European Artificial Intelligence in Medicine

conference and the journal *AI in Medicine*). Though the *Journal of the American Medical Informatics Association* (JAMIA) published papers related to cognition (see e.g., [68, 69]) as early as the late nineties, cognition was still considered as being on the periphery of informatics research. In our previous work [70], we conducted an informal evaluation of cognitive studies across three leading informatics journals over two time periods (2001-2005 and 2006-2010): *Journal of Biomedical Informatics*, *Journal of the American Medical Informatics Association* and the *International Journal of Medical Informatics*. Based on a keyword search (using common terms such as cognition, cognitive decision support, usability testing and human factors), it was found that the second time period (2006-2010) had 70% more cognition related terms than the first. As the authors argued, while not conclusive, this points towards a growth of cognitive research in recent years [70].

Additionally, the Institute of Medicine (IOM) reports of 1999 and 2011 [71, 72], highlighting the role of human cognition, accelerated the growth of cognitive science research in informatics. Influential research papers (see e.g., [73]) on the cognitive underpinnings of physician behavior further illustrated the importance of this field. More recently, the federal mandates regarding health information technology (HIT) adoption and use has reinvigorated cognitive informatics research, leading to new avenues and research directions.

As previously mentioned, our focus is on characterizing the growth, development and translation of research pertaining to cognition in biomedical and health informatics that was published in the *Journal of Biomedical Informatics* between January 2001 (when *Computers and Biomedical Research* (CBR) was reborn as JBI) and March 2014. This analysis emphasizes JBI because we performed the work for a JBI virtual issue consisting of articles previously published in the journal. Other informatics journals and conferences have published cognitive informatics papers in the same time period, but JBI has published an especially large portion of the cognitive papers since its debut in 2001, and those in JBI give a reasonable sense of general trends in the field. Since 2001, JBI has included research articles, methodological review articles, and general review articles that discussed human or team cognition, and its role in informatics. In the virtual issue that accompanies this article, we have collected a set of 57 papers. Additionally, given the breadth of topics that have been covered, we have categorized these papers along multiple cognitive dimensions. These dimensions will help in characterizing the nature of research on

cognition in biomedical informatics, current research foci, changes occurring over the past decade, and directions for future research.

2 Method

We begin by describing the process used to select the research and review articles, including the inclusion criteria, the extraction of relevant data from these articles, and their categorization into the cognitively relevant categories.

2.1 Search Process and Inclusion Criteria

We used a manual search process where we evaluated each article that was published in JBI between January 2001 and March 2014 that focused on topics related to cognition. Specifically, our definition of cognition included two aspects of cognition in healthcare contexts: (a) thinking, reasoning or decision-making, and (b) interaction with technology, collaborators or the social environment. Within these topical boundaries, we included articles with a research focus, methodological review articles and general review articles for our analysis. Editorials, commentaries and book reviews were not included. To categorize the papers, we used a broad framework that accounts for individual cognitive activities (e.g., comprehension, reasoning and decision-making), cognitive activities that are shared among a team (e.g., communication, coordination and interactions) and cognitive underpinnings of human interaction with computer systems or medical devices (e.g., usability).

2.2 Data Extraction and Synthesis

Based on the definitions, article selection was conducted in two phases. First, we identified articles that fit into one or more of the frameworks of cognition based on the title, abstract and keywords. Second, two researchers reviewed each of these articles. A final set of fifty seven ($n=57$) articles that fit our framework definitions was selected for further analysis. Of these, thirty eight ($n=38$) were research articles and the rest ($n=19$) were review articles. We followed a similar procedure in reviewing and categorizing each of the articles (with minor differences between research and review articles; details are provided below).

2.2.1 Research Articles

Each research article was read and a short summary was developed. This narrative summary included the main focus of the article, themes that were investigated, and the main findings from the study. Next, each article was categorized along multiple dimensions (see Table 1 for a full list).

The *geographical location* of the first author of the article was recorded. In the research articles selected for this review, this often coincided with the study site. The purpose of this classification was to identify the origin/source of the articles. The *cognitive framework* dimension was used to describe the foundational aspect of cognition that was used: comprehension, decision-making, distributed cognition, errors, training or usability evaluation. We provide a brief overview of each of these categories. Articles that discussed how individuals or groups perceived, comprehended and used information from the clinical environment or health IT were classified under *comprehension*. Studies on medical *decision-making*, both within clinical contexts (e.g., diagnosis, use of tools for decision support) and outside (e.g., lay public's decision-making under various public health situations), were classified as such. *Distributed cognition* encompassed articles that described the distributed nature of clinical activities, both among individuals and teams. Articles that focused on cognitive underpinnings and factors that led to *errors* were classified as such. *Usability* studies captured the design or evaluation of the cognitive aspects of health IT or decision support user interfaces. Articles that did not fall into any of these categories were grouped into a generic *other* category (we also categorized articles related to training and education within this category).

The *study type* dimension was used to classify the nature of study: experimental or naturalistic, with experimental studies referring to those conducted in laboratory or other controlled settings, and naturalistic studies conducted in real-world settings (e.g., clinics or hospital units). Similarly, the *setting* dimension was used to distinguish between studies that were conducted in clinical and non-clinical settings. Additionally, we noted *data collection method(s)*, *participants* (physicians, nurses, patients or other) and *funding sources* for the studies. A summary description of each of the dimensions is provided in Table 1. The framework reflects the nature of research and the epistemological foundations of CI research in the considered time period.

Table 1. Dimensions used for categorization of research articles

Data Category	Description of the Category
Geographical Location	The geographical location of the first author (coincided with the “Study Site”)
Cognitive Framework	<i>Comprehension</i> : Evaluation of aspects of human comprehension of concepts, themes or systems <i>Decision-Making</i> : Individual or team-based medical decision-making in a variety of clinical and non-clinical settings <i>Distributed Cognition</i> : Distributed activities, tasks and decisions of individuals and teams <i>Errors</i> : Nature, source and effects of errors <i>Usability</i> : Design or evaluation of cognitive aspects of health IT interfaces <i>Education/Training/Other</i> : Training (plus unclassified) effects of cognitively-based training or training approaches
Study Type	<i>Experimental</i> : Laboratory-based studies that evaluate the effectiveness of an intervention or design <i>Naturalistic</i> : Studies conducted in natural settings such as clinics or hospitals; predominantly observational studies
Setting	<i>Clinical</i> : Evaluation studies that were conducted in real-world clinical settings <i>Non-clinical</i> : Evaluation studies in laboratory or other simulated settings (mostly pertaining to experimental studies)
Data Collection Method(s)*	One or more of the following: interview, think-aloud, survey, screen capture, video recording, or observation
Participants*	Physicians, Nurses, Patients or Other (administrators, support personnel)
Funding Sources	Specific funding sources that were mentioned in the paper

* Subcategories that were not mutually exclusive

2.2.2 Review Articles

Review articles were first categorized as methodological or general reviews of a specific topic under investigation. This categorization was based on the JBI’s classification, where methodological reviews were specified as such. As the review papers were much more focused on specific themes, all the dimensions that were developed for the research articles could not be directly applied. We used a simplified set of dimensions to categorize the review articles. In addition to *geographical location* and *funding sources*, we used a modified version of the *cognitive framework* dimension for the review articles, consisting of five sub-categories: methods of cognitive analysis, comprehension, decision-making, errors and usability. The

methods of cognitive analysis category included detailed descriptions of cognitive science and psychological methods for studying the cognitive aspects of clinical work (See Table 2).

Table 2. Dimensions used for categorization of review articles

Data Category	Description of the Category
Geographical Location	The geographical location of the first author
Cognitive Framework*	<p><i>Methods of Cognitive Analysis</i>: Review of theoretically grounded approaches that could be used for cognitive analysis</p> <p><i>Comprehension</i>: Review of aspects of human comprehension of concepts, themes or systems</p> <p><i>Decision-Making</i>: Review of theories or methods of individual or team-based medical decision-making in a variety of clinical and non-clinical settings</p> <p><i>Errors</i>: Review of the nature, source and effects of errors</p> <p><i>Usability</i>: Design or evaluation of cognitive aspects of health IT interfaces, including principles of user/human-centered design</p>
Funding Sources	Specific funding sources that were mentioned in the paper

* Subcategories that were not mutually exclusive

3 Findings: Themes from Cognitive Informatics

In this section, we provide an overview of the themes and trends that have emerged from our analysis of the articles on cognition in JBI. In addition to describing the trends, we also provide examples of research under each of the dimensions that we have considered.

3.1 Overview of Articles

The number of articles published each year varied, ranging from 2 (in 2008) to 8 (in 2006), and averaged 4.8 per year ($S.D.=2$). Of these articles, 38 had a significant research focus and 19 were review articles (methodological review, $n=12$). These articles covered a range of topical areas including usability of interfaces, decision-making, medical errors, workflow, and challenges with electronic documentation.

Of the total 57 articles, a predominant number of them originated from institutions in North America ($n=49$, with a large percentage from US-based institutions, $n=44$ of 49). There were fewer contributions from Europe ($n=7$), and even fewer from Asia ($n=1$).

3.2 *Study Participants*

Research studies used physicians, nurses, patients or other participants (e.g., administrators, medical students, physician assistants, health agency personnel, lay public, and designers). Several studies used multiple types of participants ($n=17$ of 38; e.g., physicians and nurses). For example, Patterson and colleagues [41] used interviews and process tracing approaches with clinicians (physicians and nurses) and other healthcare professionals (information technologists and clinical application coordinators) to identify barriers to the use of clinical reminders. In another study, Malhotra and colleagues [30] interviewed clinicians (physicians and nurses), administrators and engineers to identify the issues with medical device design, use and procurement in a hospital setting. By focusing on a diverse set of stakeholders, the authors were able to capture different perspectives (e.g., different mental models) related to medical device procurement and use in clinical settings. Sheehan and colleagues [50] describe a multi-site study that evaluated the socio-technical requirements for a clinical decision support system (CDSS). In keeping with the socio-technical paradigm, they observed and interviewed emergency department (ED) physicians, nurses and administrators to identify key requirements for a pediatric CDSS.

Most of the studies used either physicians ($n=26$) or nurses ($n=17$); a significantly fewer number of studies used patients ($n=5$). For instance, Hashem and colleagues [8] described a study that had only physicians as participants. In the study, they asked 32 board-certified physicians to diagnose the same four cases, in order to test their hypothesis that physicians within a given specialty have a bias in diagnosing cases outside their own domain as being within that domain. On the other hand, Gurses and colleagues [6] reported on a study that involved only nurses. Specifically, they observed 6 nurse coordinators' use of a clinician-designed information tool, a clipboard, to support information transfer and care coordination.

Studies that used patients as participants evaluated payment decision aids [31], assessed patient perceptions of home-based health information technologies [18], patient understanding of clinical encounters [36] and patient interaction with mobile devices [10]. For example, Holzinger and colleagues [10] evaluated the use of a handheld device for collecting patient-related medical information. Similarly, Kaufman and colleagues [18] evaluated patient perceptions and challenges of the use of home-based healthcare systems. They assessed patient interactions with

a telemedicine system for diabetes patients, and identified aspects of the system that were difficult to use and impeded optimal performance.

We used a broad “other” category to include all other types of participants. As previously mentioned, this category included participants such as physician assistants, administrators and lay public. Of particular interest here are the studies that evaluated lay people’s understanding of health concepts and diseases. For example, in a study by Turner and colleagues [52], health agency personnel participated to develop user-centered guidelines for the design of a communicable disease reporting system.

In summary, most research studies utilized multiple clinical healthcare practitioners with a focus towards understanding their nature of work activities and behavior. However, some interesting insights can be drawn. First, as expected, the focus was predominantly on studying behavioral and cognitive aspects of clinical personnel, as they performed their activities or interacted with health information tools such as decision support tools. Second, over time, a greater focus on patients as participants has been likely spurred by the growth of consumer health informatics. With its exponential growth of consumer facing health applications and tools, the cognitive studies that involve patients (and lay public) are likely to gather further attention.

3.3 Study Setting and Study Type

There was an almost even distribution in the research study settings ($n_{\text{clinical}}=18$; $n_{\text{non-clinical}}=20$). Studies were conducted in clinical settings such as primary care practices, intensive care units (ICUs), operating rooms (ORs), and EDs.

A predominant number of studies used a naturalistic (or observational) approach as the study method ($n=27$). These studies relied on ethnographic methods such as participant observation, shadowing, retrospective interviews and audio/video recordings. There were far fewer laboratory-based studies ($n=10$). For example, Keselman and Smith [22] conducted their study in a lab, where participants used individual computers to read two clinical documents and then constructed their understanding of these documents in their own words. In contrast, Malhotra et al. [29] used ethnographic approaches to piece together the workflow, and identified the points of knowledge sharing and integration, and potential information and workflow breakdowns. While

the approaches (i.e., laboratory and naturalistic) varied, all studies relied on developing an in-depth understanding of a phenomenon (e.g., clinical workflow or decision making).

3.4 Data Collection Methods

Data collection plays a central role in studies on human cognition. The data collection methods reflected the study purposes and foci. For example, interviews and surveys were used to retrospectively capture participant perceptions, while direct observational and verbal think-aloud methods were used to prospectively understand the underpinnings of task performance and activities of participants. Most studies relied on multiple methods to capture the intricacies of human interactions with peers, artifacts or systems. Accordingly, in our review, more than half of the studies ($n=20$ of 38) used multiple methods for evaluation, from which a smaller set ($n=4$) used three or more methods. The predominant method was interviews with participants ($n=14$), followed by field observations ($n=11$), think-aloud ($n=9$), participant surveys ($n=7$), video recording ($n=7$), and screen capture ($n=3$; specifically for usability studies). Some studies used alternative methods (total $n=11$) such as typed recollections, photographs, card sorting, gestures, and computational (natural language processing) methods. The need for comprehensive data in understanding the nuances of human cognition is reflected in that more than half of the research studies used a multi-method approach for data collection. We provide representative examples of studies that used the different data collection methods.

Pugh and colleagues [43] used interviews with surgeons to understand the complexity of intra-operative decision-making. The interviews, based on a cognitive task analysis, provided insights into the knowledge, thought processes, goals and critical decisions during surgical tasks. Similarly, Rosenbloom and colleagues [48] used in-depth open-ended interviews with physicians and nurse practitioners to characterize their use of clinical documentation tools and their perceptions on improving the efficiency of such tools. Interview data was used to identify factors that affected clinician's satisfaction with documentation tools including its availability, expressivity, structure and quality.

Think-aloud studies involved participants verbalizing their thoughts as they interacted with a system or interface. For example, Horsky and colleagues [11] used the think-aloud approach to evaluate how physicians used a computerized patient order entry interface. Based on the analysis of verbal data, the authors characterized the nature of system usage and its challenges, using a

distributed resources framework. Another study used verbal think-aloud to evaluate the diagnostic and therapeutic reasoning of physicians. Specifically, Satter and colleagues [49] used think-aloud data to compare the diagnostic skill of physicians interacting with an avatar versus physicians interacting with traditional text-only cases. Verbal think-aloud was, in general, used to capture the thought processes that underlie human reasoning or decision-making processes.

Surveys were most often used in concert with other data collection methods. For example, Karahoca and colleagues [17] used a survey (along with system usage logs) to characterize the usability of two tablet PC prototypes, one with an iconic GUI and one with a non-iconic GUI, while Holzinger and colleagues [10] used a questionnaire (with additional observation data) to characterize interactions with a mobile interface for patients.

Video recording and screen capture of interfaces were used primarily for studying the usability and interface aspects of health information systems. For example, Neri and colleagues [34] used screen capture to evaluate the usability of a new interface that helped clinicians in managing patients' genetic profiles. In addition to capturing on-screen actions (key strokes, mouse movements), verbal think-aloud data from participating clinicians were also captured. In another study, Rasmussen and colleagues [45] used screen capture for evaluating the use of an electronic whiteboard. Video recordings were used to capture physician-patient interactions [36], to characterize the coordination of activities between OR team members [9], and to evaluate tele-health tools for nurse-patient interaction [19]. The purpose of these recordings was to utilize a process-tracing approach to characterize cognitive behaviors – either from a perspective of understanding how a task evolved or to identify potential flaws in the process.

As previously described, studies in real-world settings, often used observational data ($n=11$). These studies included observation of physician decision-making [4], ICU workflow [29], use of clinical reminders [41], coordination of team activities [9], and use of health IT (e.g., [10]). These observational studies relied on one or two researchers observing specific clinical activities (e.g., use of clinical reminders) or actively shadowing clinicians during their work activities (e.g., developing a model of clinical workflow).

Multi-method studies were the norm in most of the studies that evaluated the cognitive underpinnings of clinical activities. In a study investigating the use of an information tool for nurse coordinators [6], participant observation, shadowing and photographs of artifacts were

used as data. In a similar multi-method study, observations, interviews and questionnaires were utilized for evaluating the use of clinical reminders [41]. The use of multiple methods in these studies helped in triangulating data to develop a comprehensive understanding of the process/task.

In summary, the data collection methods revolved around mechanisms that could help in capturing a rich, nuanced perspective of clinical work – relying on multiple methods that supported the researchers in their predominantly observational methods. The emphasis on usability, especially in recent years, has shifted the focus from development of tools and mechanisms to unobtrusively collecting data as users perform various tasks (e.g., the use of screen capture tools such as Techsmith’s Morae). This shift reflects a focus on understanding the causal underpinnings of activities by taking a more nuanced approach to studying clinical activities (e.g., evaluating mouse clicks to identify EHR use breakdowns).

Data collection methods seem to reflect the research purposes undertaken by the studies: retrospective studies have relied on interviews and surveys, while prospective studies have utilized direct observations (using ethnographic approaches), think-aloud protocols and usability testing approaches (e.g., screen capture, eye-tracking).

3.5 Cognitive Framework for Research Articles

We used multiple frameworks to categorize and describe the foundational aspects of cognition used in research and review articles. In research articles, the frameworks consisted of the following: comprehension, decision-making, distributed cognition, errors, training and usability evaluation. We describe the nature of research on cognition under each of these categories using appropriate examples. A full list of the categorization of all research articles is provided in Table 3.

3.5.1 Comprehension

There were four ($n=4$) research studies that used comprehension as the key aspect of cognition. These included studies on professionals’ and nonprofessionals’ (e.g., lay public) *comprehension of clinical concepts* [22, 36], on *concept mapping* [3] and on *automated methods* to simulate expert clinical comprehension [2]. These studies were rooted in the detailed analysis of verbal and text data that were products of human reasoning and comprehension. For example,

Keselman and Smith [22] evaluated lay people's comprehension of clinical documents, and developed a classification scheme of errors in lay persons' comprehension. The classification scheme consisted of 9 categories and 23 subcategories, with the most common error being incorrect recollection of brand names of medications. Similarly, Patel and colleagues [36] investigated physician-patient interactions and their respective understanding of clinical concepts. Based on detailed analysis of physician-patient encounters, they identified structural differences in the nature of explanations that were generated – with physicians relying on causal pathophysiological structures, and patients utilizing a simple narrative style (highlighting the disruptions in their lifestyle) for their explanations. Ewing and colleagues [3] used a card-sorting methodology to categorize the differences between physicians and nurses in their mental mapping of clinical concepts. In contrast to the other studies, Cohen and colleagues [2] developed and evaluated an algorithmic approach to simulate expert clinical comprehension. They developed and used latent semantic analysis to simulate and model expert's comprehension of psychiatric narrative.

3.5.2 Decision-Making

There were nine ($n=9$) research studies that focused on decision-making. These included studies on *lay people's decision-making* during epidemics [51], on the *nature of decision-making* [4, 8] and on *physician decision-making* [13, 49]. For example, Slaughter and colleagues [51] investigated decision-making behaviors of lay people during the SARS epidemic, and found that decisions involved significant information gathering. Comprehension was characterized as interactions between lay people's information gathering behavior, their understanding of the disease, and their interpretation of their actions during the epidemic.

Other studies sought to reveal the nature of physician decision-making in clinical settings. Franklin and colleagues [4] focused on the nature of decision-making by physicians in an ED. Based on ethnographic shadowing data, they found that a significant number of decisions made by ED physicians were unplanned and opportunistic. These unplanned decisions can potentially impact the quality, safety and efficiency of clinical activities in the ED. Hashem and colleagues [8] evaluated the decision-making biases of physicians. They tested the hypothesis that physicians within a given specialty have a bias in diagnosing cases outside their own domain as being within that domain. They found evidence regarding such a bias.

Other studies evaluated methods for improving physician decision-making. For instance, Satter and colleagues [49] used avatars as simulated patients to evaluate primary care practitioners (PCPs) diagnosis, decision-making and management of mental health disorders. Compared to PCPs who were given only text-based cases, PCPs who used the avatar interface were better at diagnosing mental health disorders. The simulated environment provided a viable, and cognitively plausible, environment for training PCPs to be adept at recognizing mental health illnesses among their patients. Similarly, Jalote-Parmar and colleagues [13] evaluated an intra-operative visualization system (IVS) for a minimally invasive surgery and found improved decision-making when the IVS was used, compared to the traditional ultrasound-guided procedure. The studies on decision-making by the lay public and by clinicians had important implications for either the design of public health tools or novel informatics decision-support tools.

3.5.3 Distributed Cognition

There were six ($n=6$) research studies that employed the distributed cognition framework. These included studies on the *cognitive complexity of medical information systems* [11] and on *workflow* [19, 29].

Horsky and colleagues [11] used the distributed cognition framework to analyze the cognitive complexity of computer-assisted provider order entry. They found that the commercial order entry system used in their study had a configuration of resources that placed unnecessarily heavy cognitive demands on users. Malhotra and colleagues [29] modeled the workflow of a critical-care environment using elements of distributed cognition. They presented a cognitive workflow model with zones of interactions and processing, and this model can be used to identify medical errors. Similarly, Kaufman and colleagues [19] developed a framework for studying workflow, drawing on distributed cognition. They used this framework to analyze the workflow of tele-mediated clinician-patient encounters, which revealed barriers to productive use of tele-health technology.

3.5.4 Errors

There were four ($n=4$) research studies that focused on the cognitive underpinnings of error. These included studies on the *identification or classification of errors* [15, 42], on *error generation and recovery* [37] and on *perceptions of error* [26].

Peleg and colleagues [42] investigated errors made by a medical expert when creating clinical algorithms from narrative guidelines. They identified and then categorized the errors using Knuth's classification scheme. Kahol and colleagues [15] evaluated trauma cases for deviations from protocol and investigated the extent to which the deviations were classified as innovations as opposed to errors. They found that the extent of the deviations from the standard was influenced by clinicians' expertise, with experts' deviations being a combination of innovations and errors, and novices' deviations being mostly errors. Similarly, Patel and colleagues [37] presented a cognitive framework for the study of errors and error recovery. For instance, they found that experts (e.g., attending physicians) had a faster error recovery pattern than novices (e.g., residents). In other words, experts corrected errors as soon as they were detected. These results have important implications for the design of training interventions that can assist novices to identify, manage and recover from errors.

Laxmisan and colleagues [26] investigated differences in perceptions of error between clinicians and nonclinical healthcare professionals such as administrators and engineers, in making medical device purchasing decisions. The authors found that the clinicians focused on human aspects of error, whereas nonclinical health professionals focused on device-related aspects. These studies, using different cognitive methods, provide insights on the nature of mismatches between the users (i.e., clinicians) and decision makers (i.e., administrators), and has implications for development of healthcare policies.

3.5.5 Usability/User-Centered Design

There were ten ($n=10$) research studies that focused on usability evaluation or design issues. These included studies that compared usability of existing *medical devices* [55], that compared usability of *prototypes* [17, 27], and those that explored *usability issues over time* [45]. Zhang and colleagues [55] compared two infusion pumps by using a modified version of heuristic evaluation, which is a method commonly used to evaluate software usability. They identified each pump's usability problems as well as the severity of those problems, and found one pump to

have more problems than the other. Similarly, Lin and colleagues [27] compared a commercially available analgesia device with a prototype of a new interface, where the new interface not only eliminated drug concentration errors, but also led to fewer total errors and faster performance. Rasmussen and Kushniruk [45] explored how an electronic whiteboard's usability issues changed over time. They found that as users gained more experience with the system, user-related usability issues seemed to change. However, they show that *system*-related usability issues did not change over time.

There were three (n=3) research articles that could not be categorized within the above mentioned frameworks we established. One such example was the study by Gurses and colleagues [6], describing the design characteristics and usage of a clinician-designed information tool (specifically, a clipboard). Through shadowing and interviews with nurse coordinators who assembled the clipboard, the authors were able to identify their design goals. One of the key findings was the nurse managers' need for tools that provided quick, easy and portable information access.

3.6 Cognitive Framework for Review Articles

There were nineteen (n=19) review articles that focused on cognitive analysis, comprehension, decision-making, errors, usability, or user-centered design (See full list of articles in Table 4). The review articles provided theoretical foundations regarding the cognitively oriented methodologies and frameworks. For instance, Xiao [53] utilized a framework for *cognitive analysis* in exploring the role of physical artifacts in collaborative work in healthcare. Xiao shared many implications, one of them being that new technology should support functions previously provided by physical artifacts. Keselman, Slaughter and Patel [21] focused on *comprehension* as they presented a framework for research on lay people's comprehension of crisis information, particularly emphasizing the value of using structured qualitative methods including in-depth interviews about real situations. Gutnik, Hakimzada, Yoskowitz and Patel [7] presented a comprehensive theory of *decision-making* that included the role of emotion. Based on examples from research on sexual risk-taking behavior, they found that cognition and emotion are *both* critical to making decisions under risk and uncertainty. Murff, Patel, Hripcsak and Bates [32] reviewed methodologies for detecting adverse events (or *errors*) by discussing the advantages and limitations of existing methods. They reported that

cognitive and systems methods could result in major safety benefits because these inform the development of interventions. Zhang and Walji [57] focused on the issue of *usability* and developed a theoretical framework for electronic health records (EHR) usability. They called this framework TURF: Task, User, Representation, and Function. Finally, Horsky and colleagues [12] focused on *user-centered design*, reviewing current design principles for clinical decision support related to medication prescribing. They presented the most important design principles such as the use of controlled terminology. In general, the review papers, like the research papers, followed a general pattern of moving towards the need of applying cognitive frameworks and principles to the design and evaluation of HIT.

3.7 Research Support

Most of the research ($n=28$ of 38) and review articles ($n=12$ of 19) reported one or more funding sources. Research support came from federal agencies (e.g., National Institutes of Health or one of its Institutes (e.g., National Library of Medicine), National Science Foundation (NSF), Office of the National Coordinator (ONC), Centers for Disease Control (CDC), Veterans Affairs (VA), US Army), or private agencies and foundations (e.g., James S. McDonnell Foundation). The funding mechanisms varied, ranging from doctoral and post-doctoral training support to multiple federal grant mechanisms (e.g., R01 or R03) to large multi-site collaborative support.

3.8 Summary: General Trends in CI Research

In order to highlight the key topics and themes that were covered in the last twelve years from JBI, we created a tag cloud (weighted according to the frequency of terms) based on the titles of all articles included in our review (See Figure 1). As can be seen from the figure, the key dimensions that were used in our framework – decision-making, usability, distributed cognition, comprehension, and errors – were prominent.

With a small sample of articles ($n=57$) over a fairly long time period ($n=12$ years), it was relatively difficult to identify quantitatively based temporal trends or patterns. However, we developed qualitative trends of research themes that evolved over the last decade. In order to systematically perform this analysis (separately for research and review articles), we divided

comprehension to differentiate physicians' and patients' understanding of biomedical concepts. Other researchers have also used similar foundational approaches (e.g., [3, 11]). Another related aspect was the transformation of the methods that were used, especially in the case of usability evaluation. While early approaches relied on analytic techniques (e.g., heuristics) along with cognitive approaches (e.g., walkthroughs), recent research has adapted to the advances in technology. For example, recent research has utilized advanced screen capture tools, eye-trackers and remote-sensing tools. On a related note, we found that much of the usability evaluation of medical devices happened during the early years ($n=5$), and such studies have tapered off more recently ($n=1$). This potentially points to the significant impact that such studies (especially studies on infusion pumps) may have had on the industry in achieving improvements in patient safety on those devices. Another transformation that occurred between the early and the current phases was the widespread use of clinical information systems. While early studies on usability, especially those with clinical systems, were conducted in the laboratory (e.g., Lin et al), more recent studies have utilized a more applied, in-situ approach (e.g., see the usability evaluation of a whiteboard by [45]).

In contrast, the review articles present a different picture – both from a quantitative and qualitative perspective. Review articles were prominent during the early years ($n_{early}=15$ $n_{current}=4$) and focused on a variety of foundational cognitive science theories and methods (e.g., paradigms of cognition, cognitive analysis methods, taxonomy of errors). It is likely that these review articles provided a significant foundation for cognitive research in informatics, which was utilized in later research. The above-mentioned evaluation based on the *early* and *current* classification of JBI papers provides only one perspective of the growth of the cognitive informatics field. A more detailed evaluation by considering other journal articles published during the same time period, along with a more granular analysis, can provide a more in-depth and complete description of the development of the CI field.

4 Discussion

In this section, we summarize the findings within the context of the current areas of research, future research directions, challenges that are currently faced by researchers, and the challenges for cognitive informatics research (and researchers) in health and biomedicine. The research articles on which these findings are based are listed in Table 3.

4.1 Current Areas of Research

Based on our review of trends and patterns of CI papers in JBI, which publishes several articles by international authors, cognitive research in biomedical informatics appeared to be situated primarily in the United States, with a significant focus on studying the cognitive behaviors, activities and tasks of clinicians (nurses, physicians and other related clinical personnel). Most of these studies were also conducted within clinical settings, showing rich contextual depth in the investigations. Additionally, studies were generally observational in nature, relying on in-depth data collection (often using multiple methods to triangulate the data), and detailed multi-stage analysis (often using detailed linguistic and cognitive analytic methods).

In terms of the key research themes, most research contributions fell under usability, decision-making and team/distributed activities. The focus on usability topics is especially interesting, given the significant recent focus on the usability issues of HIT. As previously described, an uptick in the number of usability articles has also been aligned with significant upgrades in data collection tools, and also new analytic approaches. For example, several studies have described the use of unobtrusive monitoring and capturing of on-screen actions (e.g., key strokes and mouse clicks) that are used to trace and model navigational and interactive behaviors. Additionally, researchers have also developed models and frameworks that can be used (e.g., see TURF [57]) for characterizing the features of highly usable systems. Moving forward, the use of such methods need to be expanded to be widely applicable in clinical environments. It is also important to note that only a few articles discussed errors ($n=4$) even though it is a highly relevant topic with cognitive underpinnings [74]. This may also point to the relative lack of a cognitively-oriented focus in the literature reporting studies on error [75].

Most of the articles had an explicit theoretical framing – drawing on cognitive science theories related to human comprehension (e.g., theories of human memory, learning theories), problem solving (e.g., expertise), decision-making (e.g., heuristics & biases, naturalistic decision making, prospect theory), tasks and activities (e.g., cognitive task analysis, Goals, Operators Methods and Selection Rules, GOMS), and team/distributed work (e.g., distributed cognition). The use of foundational theories was also apparent in the choice of methodologies, as theory drives the methods. For example, methods such as verbal protocol analysis [38] and semantic network analysis [1] have their foundations in core theories of human comprehension, problem

solving and language. Similarly, even though much of the work on usability of EHRs can be considered applied, the use of methods such as Cognitive Task Analysis (CTA) and think-aloud techniques shows the theoretical grounding of these studies (e.g., reasoning). Additionally, the methodological review articles provide significant insights into the foundational underpinnings of the methods, their purpose and their appropriateness under various circumstances. The methodological review articles also serve an important function for the general informatics audience, who are not always familiar with the details of cognitive methods and theories.

4.2 *Future Directions for Research*

With the changing landscape of healthcare, CI researchers have significant opportunities for cognitive research. We highlight four areas that are likely to be central to CI research in the future. *First*, as previously described, the adoption and use of EHRs has increased over the last decade. That increase will likely continue over the next several years with mandated programs like meaningful use (MU), and the establishment of health information exchanges (HIE). With lingering concerns regarding the effectiveness, quality and safety afforded by EHRs, CI research can play a central role in the design and development of useful and usable interfaces for EHRs. While usability and other interface design issues have been a central theme in the past research, we are likely to see a significant increase in usability research in clinical environments with newer techniques and tools (see e.g., [76]). Along the same lines, research related to the EHR use such as information seeking [77, 78], care transitions [79-82], and human factors [83] approaches to patient safety are likely to receive more attention.

Second, a recent IOM report on “Patient Safety and Health IT” has highlighted the potential for HIT to be a double-edged sword – both as having potential for improving patient safety and also causing patient harm. With the current literature being inconclusive about the impact of HIT on patient safety, cross-disciplinary research from CI can inform the design, testing and use of HIT. Additionally, methods of process assessment that enables continuous monitoring and evaluation will mark a significant contribution by the CI community.

Third, one of the recent trends in healthcare has been the increasing role played by patients (and the public in general) in their care process. Such an involvement has been afforded by the development of consumer-based health informatics tools and applications (e.g., websites, portals and social networking tools). The proliferation of mobile and handheld devices has also provided

a new mode for the access of health information. For example, mobile devices now incorporate sensors that can track human activity and health related variables (e.g., heart rate) and provide contextually-aware support for clinical conditions (see e.g., [84] for examples on mobile support for mental illnesses). This provides significant opportunities for CI researchers along multiple dimensions including the design and evaluation of consumer health tools (both web-based and mobile), developing cognitively plausible intervention strategies that can reach the right audience (e.g., mobile tools for smoking cessation or depression support), and the design and evaluation of remote monitoring tools that can help clinicians keep tabs on patients (especially among older adults).

Fourth, bioinformatics has been a rapidly growing area in the last several years. Addition of genomic data to the clinical databases has changed the models of information organization, affecting the clinical reasoning and decision-making processes. With these developments, there is a new need to characterize and identify how clinicians reason with their data, make efficient decisions and how their tasks can be more effectively supported within the context of clinical practice. Additionally, challenges also exist in the use of effective visualization and filtering tools that can assist researchers engaged in bioinformatics research. Cognitive approaches are likely to provide a sustainable method for iteratively improving these tools' design, use and adoption, and more research in this space is likely to emerge.

4.3 Challenges for Cognitive Informatics Research

While the research on cognitive aspects of clinical activities and tasks covered a broad spectrum of healthcare activities, there were several challenges that were, explicitly and implicitly, mentioned. We provide a brief summary of the key challenges for conducting CI research.

First, studies investigating the cognitive foundations of clinician behavior require significant investments in *time*, *effort* and *planning*. Most studies utilize multiple perspectives to capture rich contextual data from real-world clinical settings on the process under investigation. Conducting a cognitively oriented study requires significant buy-in from a clinician champion, training of personnel to understand the work and activities in the setting, and developing familiarity with the clinical personnel in the setting. Additionally, after the data are collected, most studies require significant investments for analysis including transcription of voluminous

verbal data (e.g., from think-aloud, interviews, interactions), and coding and analysis of the collected data. The significant training and experience that is required for conducting data collection using these methods cannot be overstated.

Second, cognitive studies are often conducted with smaller samples, often raising questions and concerns regarding their *external validity*. These concerns arise from having limited number of participants and on the use of data from a single setting. While the studies on cognitive behavior have high relevance – reflecting the nature of real clinical practice, with clinical practitioners – the transferability of the findings are often questioned, especially during a review process (e.g., assessment of scientific paper submissions or grant applications). As we have noted, the focus of cognitive studies have been on depth and detail, developing a critical understanding of work activities, processes or strategies. A broader understanding and acceptance of cognitive research, especially among the clinical audience, may require further exposure through various channels regarding the value and purpose of such research. Cognitive studies often do not use the regular “hypothesis-testing” paradigm, and they sometimes question traditional wisdom.

Third, as previously mentioned, part of the significant cost of planning and time requirements for cognitive studies arises from obtaining the necessary *permissions* from institutional review boards (IRB). While randomized controlled trials (RCT) and experimentally oriented study designs have specific study hypotheses and familiar analysis procedures, cognitive studies often tend to be more exploratory and driven by general questions of human cognition in clinical settings. Additionally, cognitive studies rely on in-depth analysis of products of human cognition – thoughts, tasks and actions (e.g., on-screen interactions with an EHR or when performing patient-related tasks), or communication. Capturing such data falls under the “protected health information” (PHI) category and requires additional guarantees of protection – steps for de-identification of personally identified information regarding patients or providers, the use of encryption in the storage of data, and the creation and management of a system security architecture that still allows for the appropriate retrieval of data by the study personnel. While clinical settings and hospitals typically have the necessary infrastructure to achieve these requirements, the setup and maintenance of such an infrastructure in non-clinical settings require significant cost and incremental support by technical personnel.

In addition to the challenges for conducting research, CI research is going through a transformational phase – addressing new health and biomedical problems by adapting old methodologies and developing new ones. The sustainability of this adaptation is dependent on two factors: *first*, the ability of CI researchers to be cognizant of the developments in the basic scientific disciplines that they draw their research (i.e., cognitive science, psychology and learning sciences and HCI). Such developments in the fundamental research domains need to be effectively incorporated into mainstream CI research and practice. Failing to do so would lead to greater gaps between theory and CI practice, which would substantially inhibit the growth of CI as a field. A classic example is that of Bloom’s taxonomy, originally developed in the mid-1970s, and updated over the last decade – but one can find examples of research that still utilize the original taxonomy. Additionally, what is of greater concern is that there is a significant focus, especially recently, on merely applying the methods and approaches – often in a “quick and dirty” fashion – without having much of an understanding of the scientific foundations of the methods. Widely read journals such as the JBI provide an appropriate venue for presenting original theoretical frameworks and their applicability for CI researchers.

Second, as the field of biomedical informatics matures, there is a need to critically examine directions for *training and educating* future practitioners and researchers. The current educational programs in biomedical informatics (by our quick survey), especially at the graduate level, create limited opportunities for learning about CI. Most of these programs have limited focus on the CI related topics such as HCI, cognition and decision making, cognitive models for enhancing decision support, information management and cognitive load, or human factors. As a result, there is a significant concern regarding the qualifications and expertise of the next generation of researchers who would be involved in designing and evaluating healthcare environments, systems and tools.

5 Conclusions

The role of cognitive and social sciences in the study of complex healthcare activities and processes has been well acknowledged [71, 72, 85]. An evaluation of the current literature in biomedical informatics, with a representative, large sample of 57 articles over the last decade from the *Journal of Biomedical Informatics*, has highlighted the importance and growing role of cognitive and learning sciences. While its acceptance into the mainstream informatics research

literature is relatively recent, its impact has been significant – from characterizing the limits of clinician problem-solving and reasoning behavior, to describing coordination and communication patterns of distributed clinical teams, to developing sustainable and cognitively-plausible interventions for supporting clinician activities. The growth of the field within biomedical informatics, now often referred to as cognitive informatics, has not been without challenges (most of which we raised in the discussion section on “grand challenges”). However, with a broader acceptance and awareness of this field, we believe some or most of these challenges will be overcome. New topics of research such as wearable technology and the use of mobile devices have opened up new avenues and opportunities for research. Additionally, the role of simulations, both as a mechanism for understanding cognitive phenomena and as a training mechanism, is also a promising area of current research.

The *Journal of Biomedical Informatics* has played a key role in promoting and sustaining research in cognitive informatics. This is represented not only by the volume of publications but also by the quality and breadth of cognition related topics that have been covered in this journal. Within the same time period, a cursory perusal of similar informatics journals finds that they have accepted and published far fewer articles in this topical area. While the reasons for this may vary, the key role played by the *Journal of Biomedical Informatics* is clear. This exploratory review, which started with a purpose of assembling the key cognitively-oriented articles published in this journal for a special virtual issue, turned into an opportunity to reflect on the growth of this field over the last decade.

6 Acknowledgments

The writing of this manuscript was supported by a grant from the James S. McDonnell Foundation on Cognitive Complexity and Error in Critical Care (Grant 220020152). We would like to thank Cindy Guan for her editorial support and her assistance with the analysis of the data.

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Table 3. List of research articles and their categorization

Year	Authors	Country	Framework	Setting	Study Type
2001	Lin et al	Canada	Usability Evaluation	Non-Clinical	Experimental
2001	Mathews et al	Canada	Usability Evaluation	Non-Clinical	Experimental
2002	Patel et al	USA	Comprehension	Clinical	Naturalistic
2003	Zhang et al.	USA	Usability Evaluation	Non-Clinical	Naturalistic
2003	Ewing et al.	UK	Comprehension	Non-Clinical	Experimental
2003	Hashem et al.	USA	Decision Making	Non-Clinical	Experimental
2003	Horsky et al.	USA	Distributed Cognition	Non-Clinical	Experimental
2003	Kaufman et al.	USA	Distributed Cognition	Non-Clinical	Naturalistic
2003	Keselman et al.	USA	Decision Making	Clinical	Naturalistic
2005	Malhotra et al.	USA	Decision Making	Clinical	Naturalistic
2005	Rose et al.	USA	Usability Evaluation	Clinical	Naturalistic
2005	Patterson et al.	USA	NA	Clinical	Naturalistic
2005	Slaughter et al.	USA	Decision Making	Non-Clinical	Naturalistic
2005	Laxmisan et al	USA	Errors	Clinical	Naturalistic
2006	Linder et al	USA	Usability Evaluation	Clinical	Naturalistic
2006	Peleg et al	Israel	Errors	Non-Clinical	Naturalistic
2007	Malhotra et al	USA	Distributed Cognition	Clinical	Naturalistic
2007	Rosenbloom et al	USA	NA	Clinical	Naturalistic
2007	Hazelhurst et al	USA	Distributed Cognition	Clinical	Naturalistic
2007	Giani et al	Italy	NA	Non-Clinical	Naturalistic
2008	Cohen et al.	USA	Comprehension	Non-Clinical	NA
2009	Kaufman et al	USA	Distributed Cognition	Clinical	Naturalistic
2009	Gurses et al.	USA	NA	Clinical	Naturalistic
2009	Kahol et al.	USA	Training	Non-Clinical	Experimental
2010	Karahoca et al.	Turkey	Usability Evaluation	Non-Clinical	Experimental
2010	Jalote-Parmar et al.	Netherlands	Decision Making	Non-Clinical	Experimental
2011	Holzinger et al.	Austria	Usability Evaluation	Non-Clinical	Naturalistic
2011	Pugh et al.	USA	Decision Making	Non-Clinical	Naturalistic
2011	Franklin et al.	USA	Decision Making	Clinical	Naturalistic
2011	Kahol et al	USA	Errors	Clinical	Naturalistic
2011	Patel et al	USA	Errors	Non-Clinical	Experimental
2012	Satter et al.	USA	Decision Making	Non-Clinical	Experimental
2012	Keselman et al.	USA	Comprehension	Non-Clinical	Naturalistic
2012	Neri et al.	USA	Usability Evaluation	Clinical	Naturalistic
2012	Rajkomar et al.	UK	Distributed Cognition	Clinical	Naturalistic
2013	Rasmussen et al.	Denmark	Usability Evaluation	Clinical	Naturalistic
2013	Sheehan et al.	USA	Decision Making	Clinical	Naturalistic
2013	Turner et al	USA	Usability Evaluation	Non-Clinical	Naturalistic

Table 4. List of review articles and their categorization

Year	Authors	Country	Framework
2001	Patel et al.	USA	Cognitive Analysis
2001	Kushniruk	Canada	Cognitive Analysis
2002	Zhang	USA	Comprehension-Representation
2002	Patel et al.	USA	Decision Making
2002	Kintsch et al	USA	Comprehension-Representation
2003	Murff et al.	USA	Errors
2004	Zhang et al.	USA	Errors
2004	Kushniruk & Patel	Canada	Usability/User Interface
2005	Arocha et al.	Canada	Cognitive Analysis
2005	Xiao	USA	Cognitive Analysis
2005	Rinkus et al.	USA	User Centered Design/HCD
2005	Nemeth et al.	USA	User Centered Design/HCD
2005	Keselman et al.	USA	Comprehension-Representation
2005	Johnson et al.	USA	Usability/User Interface
2006	Gutnik et al.	USA	Decision Making
2008	Patel et al.	USA	Cognitive Analysis
2009	Patel et al.	USA	Cognitive Analysis
2011	Zhang & Walji	USA	Usability/User Interface
2012	Horsky et al.	USA	User Centered Design/HCD