Contents lists available at [SciVerse ScienceDirect](#)

Artificial Intelligence in Medicine

journal homepage: www.elsevier.com/locate/aiim

Understanding the nature of information seeking behavior in critical care: Implications for the design of health information technology

Thomas G. Kannampallil^{a,*}, Amy Franklin^b, Rashmi Mishra^c, Khalid F. Almoosa^d, Trevor Cohen^b, Vimla L. Patel^a

^a New York Academy of Medicine, 1216 5th Avenue, New York, NY, USA

^b School of Biomedical Informatics, University of Texas Health Science Center, Houston, TX, USA

^c School of Public Health, University of Texas Health Science Center, Houston, TX, USA

^d Medical School University of Texas Health Science Center, Houston, TX, USA

ARTICLE INFO

Article history:

Received 29 March 2012

Received in revised form

14 September 2012

Accepted 17 October 2012

Keywords:

Information seeking

Critical care

Distributed cognition

Knowledge organization

Complexity

ABSTRACT

Objective: Information in critical care environments is distributed across multiple sources, such as paper charts, electronic records, and support personnel. For decision-making tasks, physicians have to seek, gather, filter and organize information from various sources in a timely manner. The objective of this research is to characterize the nature of physicians' information seeking process, and the content and structure of clinical information retrieved during this process.

Method: Eight medical intensive care unit physicians provided a verbal think-aloud as they performed a clinical diagnosis task. Verbal descriptions of physicians' activities, sources of information they used, time spent on each information source, and interactions with other clinicians were captured for analysis. The data were analyzed using qualitative and quantitative approaches.

Results: We found that the information seeking process was exploratory and iterative and driven by the contextual organization of information. While there was no significant differences between the overall time spent paper or electronic records, there was marginally greater relative information gain (i.e., more unique information retrieved per unit time) from electronic records ($t(6) = 1.89$, $p = 0.1$). Additionally, information retrieved from electronic records was at a higher level (i.e., observations and findings) in the knowledge structure than paper records, reflecting differences in the nature of knowledge utilization across resources.

Conclusion: A process of *local optimization* drove the information seeking process: physicians utilized information that maximized their information gain even though it required significantly more cognitive effort. Implications for the design of health information technology solutions that seamlessly integrate information seeking activities within the workflow, such as enriching the clinical information space and supporting efficient clinical reasoning and decision-making, are discussed.

© 2012 Elsevier B.V. All rights reserved.

1. Introduction

Human are often characterized as *informavores* [1]. We actively seek, gather, consume and share information for satisfying diverse needs [2]. The purpose of information seeking depends on, among other things, specific user needs and tasks at hand. In complex organizational contexts, the ability of humans to access and utilize the necessary task-related information leads to better productivity and performance. But, the unaided mind, no matter how competent, simply cannot focus on all available information for making optimal decisions. Cognitive barriers such as memory capacity limitations,

lack of knowledge, information overload affect the optimality of decision-making strategies.

Critical care environments represent a prototypical information-intensive, distributed and collaborative setting [3,4], where significant information is generated by health care professionals (physicians, residents, nurses, and other support staff), and from patient care related events (e.g., bed-side monitors laboratory tests, medication orders). Most often, this information is redundantly distributed across multiple sources, such as paper and electronic records, and physicians face the onerous task of finding, retrieving, and filtering the necessary information for decision-making tasks. The distributed nature of information organization in critical care settings poses significant challenges for physicians in their information seeking activities including: (a) increased patient care time resulting from longer time for finding, filtering and organizing information due to the redundancy in

* Corresponding author. Tel.: +1 212 822 7356.

E-mail address: tkannampallil@nyam.org (T.G. Kannampallil).

available information and (b) increased possibility of missing information due to the distributed nature of information. All of these significantly affect the quality of care, increase the possibility of adverse events and can potentially impact patient safety. With the increasing role of health IT and digital repositories in clinical settings, it is relevant to evaluate the role of technology in supporting (or impeding) clinical reasoning and decision-making [5].

We utilize a cognitively driven approach to characterize the efficacy of physicians' information seeking process, and the structure and nature of clinical information that is retrieved and used for decision-making tasks. While the importance of cognitive science research on understanding the nuances of reasoning and decision-making has been well established, primarily through laboratory evaluations (e.g., [6–8]), we investigate information seeking and decision-making “in the wild,” [9] by preserving the constraints of information sources and their availability that physicians encounter in their regular clinical practice.

Insights on the information seeking behavior of physicians can help in identifying the inefficiencies (e.g., process losses) in the physician information seeking process, for developing cognitive models of physicians' information choice behavior and for designing and developing integrated intelligent health IT solutions that can assist in clinical decision making. Additionally, understanding the structure and nature of information used by clinicians during this process can trigger the development of clinical systems that streamline information retrieval and visualization mechanisms.

2. Background and significance

The complexity of patient care is exacerbated in distributed, information-rich critical care environments where physicians have to find the “right information at the right time” for making timely decisions. There is significant empirical evidence that a large percentage of physicians' information needs during the patient care process is often unmet. In a highly cited study, Covell et al. [10] found that only about 30% of a physician's information needs during patient encounters were met. Gorman and Helfand [11] and Codgill et al. [12] report on similar findings based on their empirical studies. Over 70% of physicians' information needs are related to diagnosis, treatment/therapy or drug-related information [13], and time constraints [14] result in significant amount (up to 40%) of the information needs being unmet [12].

Prior research on information seeking draws on the primary assumption that a significant amount of a physician's information needs are unmet. These studies can primarily be classified into two categories: studies that describe the nature of information needs in clinical environments and those that report on the sources of clinical information. Examples of prior work for each of these categories are described below. Currie et al. [15] describe an observational study on the information needs of clinicians while using a clinical information system. They found frequent unmet clinician information needs that were either domain-specific or patient-related. In a related study, Allen et al. [16] investigated the information needs of clinicians as they were using an information system. Based on the analysis, clinician information needs were grouped into seven categories including navigational issues, cross-referencing with other objects, laboratory results, pharmacy-related questions, differential diagnosis (or alternative diagnoses), definitions of terms and miscellaneous information needs.

In the second category, a significant amount of prior research focuses on the various sources of information that were used by clinicians to cater to their information needs. These sources range from paper and electronic records, databases, research literature, professional colleagues, or text books [13]. D'Alessandro

et al. [17] categorized the information seeking behaviors of general pediatricians into time spent on using computers, digital libraries and other information sources. They found that physicians usually depend on more than one source during their information seeking process. They argued that computer resources were the most “effective and time-efficient” mechanism for information seeking. Other researchers found that clinicians relied on their peers, external text-based resources or Internet resources [18,19] for their information needs [20]. While there were differences in the nature of information needs between physicians and other clinicians (e.g., [21]), most clinicians expressed significant difficulty in obtaining “patient, domain and institution-specific information in a timely manner,” due to the difficulty in finding the right sources of information [22,23]. Prior research has also described the challenges of finding clinical information in a timely manner, especially in dynamic critical care settings. For example, Ely et al. [24] found that physicians spent on average less than 2 min pursuing clinically relevant information. In a related study, Sackett and Strauss [25] found that information resources had to be accessible within 25.4 s for bedside consultations.

While all of these studies highlight the significant challenges of information seeking in clinical environments as potential reasons for high percentage of unmet information needs, they did not investigate their causal determinants or efficiency of processes involved in clinical information seeking. One notable exception is the study by Patel et al. [5] who found differences in the nature of use of computerized and paper based records during diagnosis tasks. In a study comparing the nature of information in paper and computerized records, they found that computerized records impacted the data collection, knowledge organization and the reasoning process of the physician. Their focus was on elucidating the differences in reasoning process caused by paper and electronic records.

In summary, most prior work on information seeking investigated clinical information needs during the information seeking process and the sources of information used during this process. Our focus is on extending prior work for evaluating the process of clinical information seeking, the structure and content of information that is sought and retrieved, and the utility of the retrieved information for diagnosis and clinical decision-making tasks.

Using an empirical study of real-world information seeking tasks, we develop an information-theoretic perspective on the process of information seeking. We utilize a rational analysis approach [26] that is predicated on understanding the problem being solved, behavioral strategies that are being used to solve the problem and the most importantly, the cognitive mechanism that drives the choice and use of such strategies [26–29]. Other researchers [30,31] have utilized similar approaches utilizing the information foraging theory to evaluate the resource utilization and sharing practices of healthcare teams.

In this paper, we specifically focus on the following: (a) develop an overall perspective on the nature of information seeking in critical care contexts, (b) time utilization across various resources during the information seeking process, (c) the relative usefulness (or utility) of the information gathered from various sources during clinical decision-making, and (d) nature and structure of medical knowledge that is gleaned from the various sources.

3. Method

3.1. Setting

The study was conducted at a large academic hospital in the Gulf Coast area that had over 33,000 admissions in 2010. Our study focuses on a 16-bed “closed” [32] MICU (medical intensive care unit) managed by intensivists. In the unit, both paper and

Table 1

Information sources and their related sub-sources of information along with the specific types of information that is present in these sources.

Information source	Information sub-source	Information category (content)
Paper chart	Resident notes	History, physician exam, lab and xray results, list of diagnoses and problems, analysis and plan of care
	Attending notes	Same as residents notes, attending notes, problem list and expanded plan
	Consult notes	Data (history, physical exam, relevant labs and x-rays and other tests related to the consultant's specialty), problem list, assessment and plan
	Orders/labs	Some labs, usually of same day or day prior
	Imaging	Summary of the report or analysis by the tech
	Medications	List of relevant medication (usually an incomplete list)
	Nursing notes & physiology data	Flow sheets
Electronic record	Resident notes	Same as above, in greater detail
	Attending notes	Same as above, in greater detail (with analysis and plan)
	Consult notes	Initial notes, has full details as above, as relevant to the consultant's specialty
	Orders/labs	All labs and results – official record, from admission and prior admissions as well.
	Imaging	Pictures of images as well as reports – official records
	Medications	List of current and past medications, including dosages, routes, types
	Nursing notes & physiology data	Nursing notes, or data directly downloaded from bedside, such as vital signs (BP, pulse, oxygenation, respiratory rate), with trends over time (24 h). Also, some other test results such as glucose that are done at the bedside by the nurse.

electronic charts were simultaneously maintained and used for patient care documentation. The distribution of information across these artifacts is detailed in Table 1. At the time of this study, the MICU did not have a CPOE (Computerized Physician Order Entry) system.

3.2. Participants

Eight ($n=8$) MICU physicians participated in the study. Of the eight participants, six were senior attending physicians; one was a third-year resident and one, a clinical fellow. All participants had significant experience working in the MICU and were very familiar with the working environment. Given their training status, the data from the third-year resident was not used for our analysis. The Institutional Review Board (IRB) approved the study.

3.3. Procedure

In order to assess the kinds of information used in the diagnosis and treatment of a patient, physicians were asked to walk through the steps needed to create a clinical summary reviewing the details from a single patient case. Using a current patient in the MICU, participants developed detailed descriptions using available sources including paper charts, electronic records, and interactions with other clinicians. As the physicians worked through the case, they verbalized (“thought-aloud”) the relevant information related to

their actions [33]. For example, the participants described the past medical history of the patient and discussed its relevance (e.g., “this is a 67 year old female patient with a past history of severe diabetic problems, and is currently admitted for cardiac issues”). The participants also described the source from which they were gleaned the information (e.g., “on resident notes, looking at past medical history”) and the rationale as to why the considered information was important. Verbal think aloud techniques are commonly used in biomedical informatics research (e.g., [34,35]) and are powerful mechanisms for developing insights on human cognition and decision-making. Once all the necessary information regarding the patient was collected, physicians were asked to provide a clinical summary of the case. In the clinical summary, the clinicians provided a brief description of the patient case followed by their assessment and plan. Each verbal report was audio recorded and later transcribed for further analysis.

3.4. Data collection

Two researchers collected data between October and December of 2010. All data collection sessions were conducted after morning rounds (late morning or early afternoon). Study participants were not present during morning rounds and were unfamiliar with the cases that were assigned to them. The data collection sessions were run on three separate days using two medical cases: day 1 (three participants, *sepsis*), day 2 (two participants, *renal failure*), and day 3 (three participants, *sepsis*). While there were marginal differences between the sepsis and renal failure cases, our clinical research team (headed by an attending physician) made every effort to ensure that the patient conditions were similar and the cases were comparable across the days of data collection. For each of the cases, the participant walked through a patient who was a recent admission to the MICU (less than 48 h).

For each data collection session, one researcher wrote down detailed field notes concerning the actions of the physicians, order of sources used, other clinicians they interacted with, and any other task-related activities. Simultaneously, the second researcher captured the duration of each task using an iPad application [36]. The touch-based application supported a single-click mechanism to record the start and end-time on each source of information (e.g., resident note, see Fig. 1) using a pre-created template of sources and sub-sources. The time captured from the iPad-recording was verified by comparing it with the time on the audio recording and other field notes that were made. Verbalized transitions (e.g., “now I am going to look at the resident notes from today’s rounds”) assisted with the reconciliation across sources.

3.5. Data analysis

Audio recordings and field notes were transcribed and then verified by a physician collaborator for accuracy and completeness. Data from these recordings were organized into a structured format shown in Fig. 2. The columns represent the type of information source (paper or electronic), information sub-source (e.g., resident note), time at which the source was first accessed, the information category of the sub-source (e.g., history and physicals from resident note, based on categories provided in Table 1), the information sub-category the physicians were using (i.e., based on their verbalization) (e.g., problem list from their history and physical), and finally, the patient-specific medical information that was referred to as an “information unit.” The category and sub-category of information were based on suggestions by our clinical collaborator. These were not used in our current analysis. The “information unit” column was used to capture clinically relevant information and was used extensively in our current analysis.

Fig. 1. iPad application used for data collection.

In analyzing the data, we first separated the sources into paper and electronic categories. Following the division into this format, for each source (e.g., resident note or attending note), we identified the content including number of unique mentions of information that was verbalized from that source. For example, in Fig. 2, from the resident’s note the physician noted the following patient-condition related information: heart disease, renal failure and ESRD (provided in the “information unit” column). Further description of the identification and use of “unique mentions” of information is provided in the data analysis section.

3.5.1. Rate of information gain: time utilization for information seeking

In addition to evaluating the time spent on documentation and utilization of medical knowledge categories, we computed the information gain and utility of the retrieved information. Overall rate of information gain is a measure of the total information gathered from the various sources over a period of time. Based on the number of information units gained from each sub-source and the time spent, we computed the overall rate of information gain, G_0

$$G_0 = \frac{\text{total no. information units in sub-source}}{\text{time spent on sub-source}}$$

Here, the sub-source would include categories mentioned in Table 1 and an information unit was the clinically relevant information provided in the “information unit” column in Fig. 2. G_0 provides a measure of the overall rate of information gained from a source.

An important aspect of information rich environments is that repeated occurrence of information reduces the potential value of that information. That is, when the same information is encountered multiple times within the same document, its relative value for the reader decreases. This is the basis of Charnov’s marginal value theorem [37–39]. Detailed analysis of the use of marginal value theorem and its use in information use in a variety of decision making settings can be found in Pirolli and Card [2] or in Pirolli [40,41]. Information gain has implications for the choice of sources that are used for information gathering. While a source may contain a large quantity of information, if the overall information gain is low, then the utility of that source is likely to be lower.

We utilized the marginal value theorem to compute the relative rate of information gain (R_g) across the various sub-sources. For this, we identified the repeated information within and across sub-sources and assigned different weights to the repeated and unique information. The assignment of weights was done in the following manner: patient-condition related information that was never repeated across the whole transcript was given a score of 1 (high utility information: *Unique*); patient-condition related information

Information Source	Information Sub-Source	Start Time	Information Category	Information Sub-Category	Information Unit
Paper	Resident Note	3.3	Resident H & P	Age	Heart disease
				Problem list	Renal failure
					ESRD

Fig. 2. Transcribed format: the columns show the source, time at which the source was first used, the specific source category (e.g., resident note), the patient-specific medical information (in the “detail” column).

Table 2

Calculation of the rate of information gain and relative rate of information gain.

Sub-source	Info. units (IU)	No. of new IU	Repeat (within-source)	Repeat (across-source)	Total info. gain	Time spent (s)	Rel. info gain (R_g)
Resident note	27	24	3	0	$[24 \times 1 + 3 \times 0.5] = 25.5$	158	$[25.5/27]/158 = 0.005$

that was not repeated within the same sub-source but in a different sub-source was given a score of 0.75 (medium utility information). For example, if the heart disease was first mentioned in a resident note, and then repeated in the attending note (i.e., a different source), the second time it was used, it was given the lower score. Patient-condition related information that was repeated within the same source (e.g., heart disease repeated within same resident note again) was given a score of 0.5 (low utility information). The scoring mechanism was based on a modified version of Charnoff's marginal value theorem. *Relative rate of information gain* (R_g) was computed by dividing the information gain per sub-source, by the time spent on utilizing that source. An example of how the information gain was computed is shown in Table 2.

In our scoring mechanism, while we did weight the uniqueness of information we did not consider the relative importance of a piece of information. For example, information regarding a patient's age is perhaps less important than their past history of MI for a patient presenting with chest pain (age may also be a factor is the patient is older). While, considering the relative importance of each patient-condition related information would greatly improve our information-theoretic analysis, information importance or relevance is highly variable (by both condition and across participants). As such, we did not consider it in our current analysis.

3.5.2. Structure of medical knowledge

The patient-related detail (see "Information Unit" column in Fig. 2) was categorized using the medical knowledge framework [6,42]. It provides an epistemological framework for characterizing the knowledge used for clinical comprehension and problem solving, and represents a formalization of medical knowledge. The framework differentiates the levels at which a physician organizes the available knowledge and provides insights into the clinical practitioners' medical knowledge. We have utilized similar approaches to describe physician-patient interactions [43], diagnostic reasoning [44,45], nature of clinical expertise [45] and clinical comprehension [5]. In this paper, we utilize the framework to categorize and understand the nature of information that is retrieved by physicians during their information seeking process. This also aids in developing an understanding of the clinical reasoning processes that underlie the information seeking process.

The hierarchical framework consists of five levels of medical knowledge, with empirium at the lowest level, followed by observations, findings, facets and diagnoses at higher levels. Empirium corresponds to basic description of sensory information and often contains no medical interpretation (e.g., skin color). Observations are perceptual categories and require medical knowledge for interpretation. For example, a patient reporting dry skin or chest pain during a physician encounter. Findings are groups of observations that are interpreted in terms of their clinical significance. For example, shortness of breath is interpreted within the context of a myocardial infarction. Facets refer to cluster of findings indicating a medical condition or a cluster of conditions (e.g., embolic phenomena are interpreted from a cluster of chest pain, DVT in calf muscles and V/Q). The clustering of findings together helps in exploring a particular condition (i.e., embolic phenomena) while ignoring others. These represent general pathological conditions and help the clinician to partition the diagnosis problem space. The diagnosis level is the highest level with known therapeutic or explanatory models. The diagnosis category subsumes all the

previous categories. As reported elsewhere (e.g., [46]), this hierarchy of medical knowledge is useful for narrowing down the diagnosis search space. In other words, as the physician collects data regarding a patient, the diagnosis search space is narrowed till the final diagnosis and management decisions are made.

Consider the following example: a physician notes that a patient presented to the emergency department with chest pain, shortness of breath, leg swelling, excessive sweating and a weak pulse. As described earlier, chest pain, leg swelling and excessive sweating would be considered as observations in the framework. The presence of a deep vein thrombosis (DVT) through a Doppler scan is a finding that is developed from a preliminary observation of leg swelling. These deductions (along with other evidence) can lead the physician to reach an intermediary conclusion regarding the presence of embolic phenomena in the patient. The final stage is the diagnosis of pulmonary embolism (where one or more arteries are blocked) in the patient. A summary of the categories and a brief explanation is provided in Table 3.

All transcripts were coded using the knowledge categories provided in Table 3. By having these knowledge categories, we were able to organize the structure of medical knowledge gathered from paper and electronic records.

Two researchers coded the data into the categories described above (one a practicing Internal Medicine physician and the other a graduate student with a medical degree). There was a high degree of agreement between the coders, and any discrepancies in the coding were resolved through collaborative discussion and agreement between the coders. Given the small sample size and exploratory nature of the experimental design, comparisons between electronic and paper records between the various variables (time spent, relative rate of information gain, medical knowledge categories) were analyzed using paired *t*-tests.

4. Results

4.1. Qualitative evaluation: information seeking process

First, we provide a brief overview of the information seeking process in the MICU. Similar to what was reported in prior studies (e.g., [3,47,48]), we found that information was distributed among

Table 3

Summary of medical knowledge categories and examples.

Category	Explanation	Example
Empirium	Lowest level of information	Age
Observations	Units of information that are recognized as potentially relevant in the problem-solving context	Chest pain
Findings	Groups of observations that have potential clinical significance	V/Q (Ventilation-Perfusion) mismatch, DVT in calf muscles (Deep Vein Thrombosis on Doppler scan)
Facets	Clusters of findings that indicate an underlying problem or class of problems, often reflecting pathological descriptions ("interim hypothesis or constructs")	Embolic phenomenon
Diagnosis	Subsumes all previous levels	Pulmonary embolism

various sources: paper and electronic records, monitors, and people (nurses, pharmacists, respiratory therapists, and residents). During their information seeking process, physicians gathered information from paper charts, electronic records, through patient evaluation, and indirectly, from other clinicians involved in the care process. Based on our field notes and observations, we found that paper charts were used as the information source that contained notes by residents at patient admission, attending notes and summary, orders, tests, and other administrative material. While paper records were information-rich and mostly current, they provided the physician only a snapshot view of a patient. Most of our participants also described that the updates to the paper records were manual and, hence slow. As one of our participants noted, “I usually cannot depend on the paper charts for the most updated information. . . these are usually slow in getting up-to-date”.

In contrast, electronic charts contained updated information about test results, information from bed-side monitors and vitals. Electronic records were often used in conjunction with the paper charts to “fill-in” information that is often unavailable or missing in the paper charts. Several participants mentioned that they had to go back and forth between both sources to find the most up-to-date information, “you just learn to figure out where to find the most updated information. It may be idiosyncratic but you develop habits and preferences.” For example, we observed that the physicians sometimes switched back and forth between paper and electronic charts to find some pertinent information regarding a patient condition (or status). Most often, this was to determine whether there were updates regarding a lab test or X-ray. In addition to serving as an electronic data storage, electronic records also afforded flexible mechanisms for visual representation (e.g., zooming of x-ray images), alternate mechanisms for information representation (e.g., using graphs to visualize trends or comparisons) and structured organization of information content (e.g., orders, lab results are organized in separate tabs). As one of our participants observed, “I have to use the electronic charts for certain things such as graphs and charts as it gives the flexibility to manipulate and view from different perspectives.” Physicians also interacted with clinical support staff including fellows, residents, nurses, and respiratory therapists to update their knowledge about the patient's current condition.

4.2. Quantitative evaluation: structure of information seeking

In this section, we describe the time spent on information sources, information gain from various sources, and the nature of knowledge utilization from these sources.

4.2.1. Time spent on information sources

There was no significant difference in the overall time spent on paper when compared to electronic charts ($M_{\text{electronic}} = 661.3$ s, $M_{\text{paper}} = 528.3$ s, $p = 0.296$). As expected, more time was spent on evaluating the physician notes (both attending and resident notes) on the paper record than on the electronic record ($t(6) = 2.38$, $p = 0.05$). Meanwhile, significantly more time was spent on electronic records for retrieving information regarding orders, medications and laboratory results.

4.2.2. Rate of information gain from various sources

The overall rate of information gain, G_o , was greater for paper records when compared to electronic records ($t(6) = 3.262$, $p < 0.005$). The relative rate of information gain, R_g , was marginally greater when using electronic records ($t(6) = 1.89$, $p = 0.1$). More specifically, the relative rate of information gain for attending notes, medications and orders/labs was significantly higher in an electronic format. The differences in the other sub-sources were marginal (or non-existent). Fig. 3 shows the differences between

paper and electronic records based on the relative rate of information gain (rate was measured per second).

This effect was more prominent in the case of medications and orders/labs from the electronic records and was due to the highly structured representation that was afforded by the electronic interfaces. This was not particularly surprising as prior research has shown the positive effect of structured representation on human cognition [49]. For example, tables and graphs aid in easier interpretation and comprehension of information.

4.2.3. Knowledge utilization from various sources

There were no differences in the overall utilization of the medical knowledge categories across paper and electronic records ($t(6) = -0.22$, $p = 0.83$). The distribution of medical knowledge categories across paper and electronic records is shown in Fig. 4. Nevertheless, there were nuanced differences in the individual knowledge categories. We found that there was significantly more retrieval of medical knowledge categories related to observations ($t(6) = 4.2285$, $p < 0.001$) and findings ($t(6) = 2.2163$, $p = 0.05$) from electronic charts. In contrast, more empirium type of information was retrieved from paper charts ($t(6) = 2.5342$, $p < 0.05$). No significant differences were observed for facets or diagnosis. The difference in the nature of medical knowledge retrieved is also likely related to the functional organization of information.

Additionally, we wanted to explore if the medical knowledge categories of a certain type were retrieved from specific information sub-sources. We found a high degree of correlation between the information category (e.g., specific information within an information sub-source) in the electronic records and the medical knowledge categories: observations and medications ($r = 0.56$, $p < 0.05$); observations and orders/labs ($r = 0.57$, $p < 0.05$), findings and medications ($r = 0.66$, $p < 0.05$) and findings and orders/labs ($r = 0.61$, $p < 0.05$). Other comparisons in the electronic charts were not significant. In particular, the correlations show that structured organization of information in electronic charts prompts quicker retrieval of higher order medical information. For example, medication lists and laboratory results are organized in a structured template in electronic charts that aids in quicker reasoning and abstraction of information within the context of the clinical problem. While we cannot show causal association, this points to the fact that the organization of information potentially drives the reasoning process. We discuss this further in the next section.

5. Discussion

We investigated information seeking behavior of physicians during clinical decision-making, focusing on the time spent on various sources from which the information was retrieved, the relative information gained and the structure of medical knowledge retrieved from the various sources. We found that physicians spent relatively equal amount of time on electronic and paper records for retrieving information during their decision making process. Overall, more information was retrieved from paper records, but the information retrieved from electronic records was significantly more unique and consequently, led to a higher information gain. Additionally, we also found that there were inherent differences in the epistemology of the medical knowledge that was retrieved: physicians retrieved significantly more higher level medical knowledge (observations and findings) from electronic charts, while more basic information (empirium) was retrieved from paper charts.

An interesting deduction that can be made from our findings is the principle of local optimization during the information seeking process. Physicians optimized their information seeking process by accessing resources that they believed maximized their information gain and aided in their medical reasoning and

Fig. 3. Relative rate of information gain (i.e., information gain/time spent) of the various information sources in the MICU. The x-axis represents the various sub-sources of information and y-axis represents the information gained.

decision-making process. In other words, the information seeking process was driven by the socio-technical organization within the environment. This led physicians to depend on certain resources for certain types of information (e.g., orders and labs on electronic charts as they were highly structured). Information sub-sources that had higher information gain were utilized for retrieving certain information. For example, we found that patient medications and orders for laboratory tests and labs were retrieved from electronic records. These information sub-sources (medications and orders) were highly structured and allowed for easy access and retrieval. In the same vein, paper charts were used for retrieving basic information regarding patients (of type empirium, e.g., age). Additionally, higher level medical knowledge (e.g., findings) was more easily retrieved from structured sources leading them closer to clinical diagnosis.

Such a process of contextually centered information seeking has several disadvantages: first, it requires significant switching between resources leading to loss in time and effort; Second, considerable amount of expertise and experience is necessary before a physician settles on a successful search process and strategy; and third, there is no uniformity within this process across physicians

and hence requires a physician to constantly develop new strategies with systemic and organizational changes. It is often acknowledged that a considerable part of the information seeking process (in any environment) involves an organic adaptation to the environment that leads to learning appropriate and potentially efficient mechanisms for information seeking. While physicians showed marginal difference in the relative rate of information gain across paper and electronic charts, the significant nuances within individual information sub-sources (e.g., paper for lower level information and electronic charts for structured information) showed the propensity of physicians to adapt their information seeking strategies to synchronize with the choices available in the environment. In other words, an *adaptable* and *local* information seeking strategy is utilized.

While global optimization strategies are potentially unachievable in complex critical care settings, integrated systems that simultaneously support the cognitive and reasoning processes of physicians are likely to be highly beneficial. We discuss design implications that can potentially mitigate the inefficiencies of the local optimization during information seeking.

Fig. 4. Average number of medical knowledge categories in paper and electronic records.

5.1. Enriching the external representation

One of the important drivers for physicians depending on certain sources for certain types of information is the ease of retrieving information from these sources. For example, we found that *significantly more unique information was gained from electronic records than paper records*. As previously described, this effect was likely due to the structured representations in electronic records (for example, tables and charts). In contrast, during our observation sessions we found that physicians relied on the paper charts for reading through the notes (and briefly looked over the typed electronic notes). As one of our participants observed, “*I like to get an overall view of this patient from the paper chart and then I can look at the tests.*” This was likely due to the fact that electronic charts did not offer any specific advantages for reading the physician notes (for example, highlighting key events or information in the notes) while the paper notes afforded easy perusal through annotation and markings. Augmenting some of the electronic notes by increasing its affordability for quick reading and evaluation is likely to increase the efficacy of using electronic notes.

The concept of enrichment of a source is derived from information foraging theory [41,50] where the rate of gain of information from a resource can be improved by providing better mechanisms for information identification and retrieval. For example, organizing laboratory test results in a tabular form (with graphical plotting) helps in quicker retrieval of information than a listing of values. Providing mechanisms for structured enrichment, such as highlighting key results or important aspects of the past medical history, can potentially improve the rate of information retrieval and correspondingly lead to quicker and more accurate decisions. Similar results have also been reported by Sharda et al. [51] who found that enrichment of psychiatric narratives through structured presentations (e.g., through highlighting key concepts) led to expert-like clinical comprehension among novice clinicians. As we move toward complete electronic adoption by 2014, the importance of enriching aspects of Electronic Health Record (EHR) use is very important.

5.2. Supporting clinical decision making and reasoning

Based on our observations, we found that the information seeking process was exploratory, cumulative, and iterative. During information seeking process physicians had to constantly find and re-find information from multiple sources to confirm or invalidate their various hypotheses. In particular, physicians depended on certain sources for certain types of information resulting in them returning to previously encountered information for confirmation. For example, most physicians viewed imaging on the electronic charts and often returned to the paper charts to verify and confirm their deductions from the imaging results. Such a process led to the iterative back-and-forth switching between multiple sources (a process driven by the contextual organization of information). Such switching increases the cognitive load on physicians to effectively filter the information for diagnostic reasoning and decision-making [34,42].

In addition to the switching, the nature of the information across sources that was utilized by physicians was inherently different: we found that physicians retrieved a significant amount of lower level medical information from paper records. This points to a *data-driven* approach to reasoning about the clinical case (e.g., [43]). In contrast, the presence of significantly more high-level medical information of type “findings” suggests a *hypothesis-driven* reasoning strategy while using the electronic records. While expert clinicians can effectively manage such switching for routine cases, it can pose significant challenges for a novice (e.g., medical student) or intermediate (junior medical resident) level physicians [8].

In short, the local optimization within the information seeking process by physicians can affect the logical flow of their reasoning process (e.g., switching between data-driven and hypothesis-driven strategies). While we did not explicitly measure the effectiveness of the reasoning strategies, it is evident that the reasoning strategies were a combination of both data- and hypothesis-driven strategies. For effective development of systems and tools that support clinical reasoning and decision-making within the complex critical care domain, designers need to consider the clinical workflow and the socio-technical aspects within the design process [52].

5.2.1. Limitations

There are some limitations that we hope to address in the future iterations of this study. We did not assign different weights for information or their sources. In other words, all information was considered as equal. While, we realize this may not be the ideal, such an approach provided a baseline for establishing the viability of the information-theoretic approach for studying information seeking behavior. We have started a secondary analysis of data by re-classifying it based on its relative clinical importance. We also did not control the order in which the clinicians sought and retrieved information. It is possible that the information gain and medical knowledge structure are affected by the order in which the different sources (paper, electronic) are accessed.

Additionally, we did not have access to the complete patient record to investigate whether the information retrieved was indeed complete. It must also be noted that this study was conducted in a single MICU and further evaluation studies must be conducted to explore the generalizability of the results across settings. Nevertheless, we believe that our study is a first of its kind that investigates the information seeking process from an information-centric perspective providing insights into the rationale behind the strategies adopted during the information seeking process.

6. Conclusion

Critical care environments present significant challenges for information seeking as information is distributed across multiple sources, such as paper charts, electronic records, bedside monitors and support personnel. Physicians have to expend cognitive resources to seek, filter and organize information from various sources for making diagnostic and therapeutic decisions. Based on a study of the information seeking behavior of physicians in a MICU, we found the information seeking process exploratory and iterative. Additionally, the distributed nature of information resulted in the information seeking process driven by the local organization of information: physicians optimized their information seeking process by depending on specific sources for specific types of information and their choices were often driven by the information gain from these sources. We discussed mechanisms of enriching the clinical information space and supporting the clinical decision-making and reasoning tasks to improve the information seeking process.

Acknowledgments

This research project was partially supported by Grant No. 220020152 by James S McDonnell Foundation (JSMF) for Cognitive Complexity and Error in Critical Care to Vimla L. Patel and by Grant No. 10510592 for Patient-Centered Cognitive Support under the Strategic Health IT Advanced Research Projects Program (SHARP) from the Office of the National Coordinator for Health Information to Jia-jie Zhang. We would like to thank Archana Laxmisan and Suchita

Batwara for their help in data analysis, and Zhe Li and Naveen Kommera, for their assistance with the data collection efforts.

References

- [1] Dennett DC. *Consciousness explained*. Toronto, Canada: Little, Brown & Company; 1991.
- [2] Pirolli P, Card S. Information foraging. *Psychological Review* 1999;106:643–75.
- [3] Patel VL, Cohen T. New perspectives on error in critical care. *Current Opinion in Critical Care* 2008;14(4):456–9.
- [4] Cohen T, Blatter B, Almeida C, Shortliffe E, Patel V. A cognitive blueprint of collaboration in context: distributed cognition in the psychiatric emergency department. *Artificial Intelligence in Medicine* 2006;37(2):73–83.
- [5] Patel VL, Kushniruk AW, Yang S, Yale JF. Impact of a computerized patient record system on medical data collection, organization and reasoning. *Journal of the American Medical Informatics Association* 2000;7(6):569–85.
- [6] Evans DA, Gadd CS. Managing coherence and context in medical problem-solving discourse. In: Evans DA, Patel VL, editors. *Cognitive science in medicine: biomedical modeling*. Cambridge, MA: MIT Press; 1989. p. 211–55.
- [7] Patel VL, Evans DA, Kaufman DR. Cognitive framework for doctor–patient interaction. In: Patel VL, Evans DA, editors. *Cognitive science in medicine: biomedical modeling*. Cambridge, MA: MIT Press; 1989. p. 253–308.
- [8] Patel VL, Groen GJ. Real versus artificial expertise: the development of cognitive models of clinical reasoning. In: Stefanelli M, et al., editors. *Proceedings of the third conference on AI in medicine. Lecture notes in medical informatics*, vol. 44. Maastricht, Netherlands: Springer-Verlag; 1991. p. 25–37.
- [9] Hutchins E. *Cognition in the wild*. Cambridge, MA: MIT Press; 1995.
- [10] Covell DG, Uman GC, Manning PR. Information needs in office practice. *Annals of Internal Medicine* 1985;103(4):596–9.
- [11] Gorman PN, Helfand M. Information seeking in primary care: how physicians choose which clinical questions to pursue and which to leave unanswered. *Medical Decision Making* 1995;15(2):113–9.
- [12] Cogdill KW, Friedman CP, Jenkins CG, Mays BE, Sharp MC. Information needs and information seeking in community medical education. *Academic Medicine* 2000;75:484–6.
- [13] Davies K, Harrison J. The information-seeking behaviour of doctors: a review of the evidence. *Health Information and Libraries Journal* 2007;24(2):78–94.
- [14] Green ML, Ciampi MA, Ellis PJ. Residents' medical information needs in clinic: are they being met? *American Journal of Medicine* 2000;109:218–23.
- [15] Currie LM, Graham M, Allen M, Bakken S, Patel V, Cimino JJ. Clinical information needs in context: an observational study of clinicians while using a clinical information system. In: *AMIA Annual Symposium Proceedings*. 2003. p. 190–4.
- [16] Allen M, Currie LM, Graham M, Bakken S, Patel VL, Cimino JJ. The classification of clinicians' information needs while using a clinical information system. In: *AMIA Annual Symposium Proceedings*. 2003. p. 26–30.
- [17] D'Alessandro DM, Kreiter CD, Peterson MW. An evaluation of information-seeking behaviors of general pediatricians. *Pediatrics* 2004;113(1 Pt 1):64–9.
- [18] Dawes M, Sampson U. Knowledge management in clinical practice: a systematic review of information seeking behavior in physicians. *International Journal of Medical Informatics* 2003;71(1):9–15.
- [19] Hider PN, Griffin G, Walker M, Coughlan E. The information-seeking behavior of clinical staff in a large health care organization. *Journal of Medical Library Association* 2009;97(1):47–50.
- [20] Reddy M, Jansen J. A model for understanding collaborative information behavior in context: a study of two healthcare teams. *Information Processing and Management* 2008;44(1):256–73.
- [21] Xu X, Rocha RA, Bigelow SM, Wallace CJ, Hanna T, Roemer LK. Understanding nurses' information needs and searching behaviour in acute care settings. In: *AMIA Annual Symposium*. 2005. p. 839–43.
- [22] Ely JW, Osheroff JA, Chambliss ML, Ebell MH, Rosenbaum ME. Answering physicians' clinical questions: obstacles and potential solutions. *Journal of American Medical Informatics Association* 2005;12(2):217–24.
- [23] McKnight LK, Stetson PD, Bakken S, Curran C, Cimino JJ. Perceived information needs and communication difficulties of inpatient physicians and nurses. *Journal of American Medical Informatics Association* 2002;9(6 Supplement 1):64–9.
- [24] Ely JW, Osheroff JA, Ebell MH, Bergus GR, Levy BT, Chambliss ML, et al. Analysis of questions asked by family doctors regarding patient care. *BMJ* 1999;319(7206):358–61.
- [25] Sackett DL, Strauss SE. Finding and applying evidence during clinical rounds: the 'evidence cart'. *Journal of the American Medical Association* 1998;280:1336–8.
- [26] Anderson JR. *The adaptive character of thought*. Hillsdale, NJ: Lawrence Erlbaum Associates; 1990.
- [27] Anderson JR. *The adaptive nature of human categorization*. *Psychological Review* 1991;98:409–29.
- [28] Anderson JR. *Rules of the mind*. Hillsdale, NJ: Lawrence Erlbaum Associates; 1993.
- [29] Anderson JR, Boyle CF, Corbett A, Lewis MW. Cognitive modelling and intelligent tutoring. *Artificial Intelligence* 1990;42:7–49.
- [30] Caldwell BC, Garrett SK, Boustany KC. Healthcare team performance in time critical environments: coordinating events, foraging, and system processes. *Journal of Healthcare Engineering* 2010;1(2):255–76.
- [31] Garrett SK, Caldwell BC. Task coordination and group foraging in healthcare delivery teams. In: *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 2006.
- [32] Safar P, Grenvik A. Organization and physician education in critical care medicine. *Anesthesiology* 1977;47(2):82–95.
- [33] Ericsson KA, Simon HA. *Verbal protocol analysis: verbal reports as data*. Cambridge, MA: MIT Press; 1993.
- [34] Patel VL, Yoskowitz NA, Arocha JF, Shortliffe EH. Cognitive and learning sciences in biomedical and health instructional design: a review with lessons for biomedical informatics education. *Journal of Biomedical Informatics* 2009;42(1):176–97.
- [35] Patel VL, Zhang J, Yoskowitz NA, Green R, Sayan OR. Translational cognition for decision support in critical care environments: a review. *Journal of Biomedical Informatics* 2008;41(3):413–31.
- [36] Li Z, Robinson DJ, Zhang J. Uobserve: a mobile app for the study of emergency department workflow. In: *American College of Emergency Physicians Research Forum*. 2010.
- [37] Charnov EL. Optimal foraging: the marginal value theorem. *Theoretical Population Biology* 1976;9:129–36.
- [38] Stephens DW, Charnov EL. Optimal foraging: some simple stochastic models. *Behavioral Ecology and Sociobiology* 1982;10:251–63.
- [39] Stephens DW, Krebs JR. *Foraging theory*. Princeton, NJ: Princeton University Press; 1986.
- [40] Pirolli P. Rational analyses of information foraging on the web. *Cognitive Science* 2005;29(3):343–73.
- [41] Pirolli P. *Information foraging: a theory of adaptive interaction with information*. New York, NY: Oxford University Press; 2007.
- [42] Patel VL, Kaufman DR. Medical informatics and the science of cognition. *Journal of the American Medical Informatics Association* 1998;5(6):493–502.
- [43] Patel VL, Arocha JF, Kaufman DR. Diagnostic reasoning and medical expertise. In: *Medin D, editor. Psychology of learning and motivation – advances in research and theory*. 1994. p. 187–252.
- [44] Patel VL, Kaufman DR, Arocha JF. Emerging paradigms of cognition in medical decision-making. *Journal of Biomedical Informatics* 2002;35(1):52–75.
- [45] Patel VL, Groen GJ, Scott HS. Biomedical knowledge in explanations of clinical problems by medical students. *Medical Education* 1988;22(5):398–406.
- [46] Arocha JF, Wang D, Patel VL. Identifying reasoning strategies in medical decision making: a methodological guide. *Journal of Biomedical Informatics* 2005;38(2):154–71.
- [47] Laxmisan A, Hakimzada F, Sayan OR, Green RA, Zhang J, Patel VL. The multitasking clinician: decision-making and cognitive demand during and after team handoffs in emergency care. *International Journal of Medical Informatics* 2007;76(11–12):801–11.
- [48] Malhotra S, Jordan D, Shortliffe E, Patel VL. Workflow modeling in critical care: piecing together your own puzzle. *Journal of Biomedical Informatics* 2007;40:81–92.
- [49] Zhang J, Norman DA. Representations in distributed cognitive tasks. *Cognitive Science* 1994;18(1):87–122.
- [50] Sandstrom PE. Scholarly communication as a socioecological system. *Scientometrics* 2001;51(3):573–605.
- [51] Sharda P, Das AK, Cohen T, Patel VL. Customizing clinical narratives for the electronic medical record interface using cognitive methods. *International Journal of Medical Informatics* 2006;75:346–68.
- [52] Patel VL, Shortliffe EH, Stefanelli M, Szolovits P, Berthold MR, Bellazzi R, et al. The coming of age of artificial intelligence in medicine. *Artificial Intelligence in Medicine* 2009;46:5–17.