Chapter 18
Sub-optimal Patterns of Information Use: A Rational Analysis of Information Seeking Behavior in Critical Care

Thomas G. Kannampallil, Amy Franklin, Trevor Cohen, and Timothy G. Buchman

Introduction

Human information seeking is driven by their need to satisfy their various needs [1] related to specific tasks and activities. The effectiveness of information seeking is critical in achieving high throughput and efficiency. Nevertheless, given the plethora of available data it is impossible to effectively focus on specific data – cognitive barriers such as information load, memory capacity and strategies significantly affect the effectiveness of information seeking and gathering. While much is known about the information needs and sources of information that are typically used by

Portions of this chapter, including sections 2, 3 & 4 (along with tables and figures) appeared in Kannampallil et al. Understanding the nature of information seeking behavior in critical care: implications for the design of health information technology. *Artificial Intelligence in Medicine*. 57(1):21–9.

T.G. Kannampallil (✉)
Center for Cognitive Studies in Medicine and Public Health, New York Academy of Medicine, New York, NY 10029, USA
e-mail: tkannampallil@nyam.org

A. Franklin, PhD
School of Biomedical Informatics, University of Texas Health Science Center, Houston, TX 77030, USA

National Center for Cognitive Informatics and Decision Making in Healthcare (NCCD), Houston, TX 77030, USA
e-mail: amy.franklin@uth.tmc.edu

T. Cohen, MB ChB, PhD
School of Biomedical Informatics, University of Texas Health Science Center, Houston, TX 77054, USA
e-mail: trevor.cohen@uth.tmc.edu

T.G. Buchman, PhD, MD, FACS, FCCP, MCCM
Emory Center for Critical Care, Emory University School of Medicine, Woodruff Health Sciences Center, Emory University, Atlanta, GA 30322, USA
e-mail: tbuchma@emory.edu

V.L. Patel et al. (eds.), *Cognitive Informatics in Health and Biomedicine*, Health Informatics, DOI 10.1007/978-1-4471-5490-7_18,

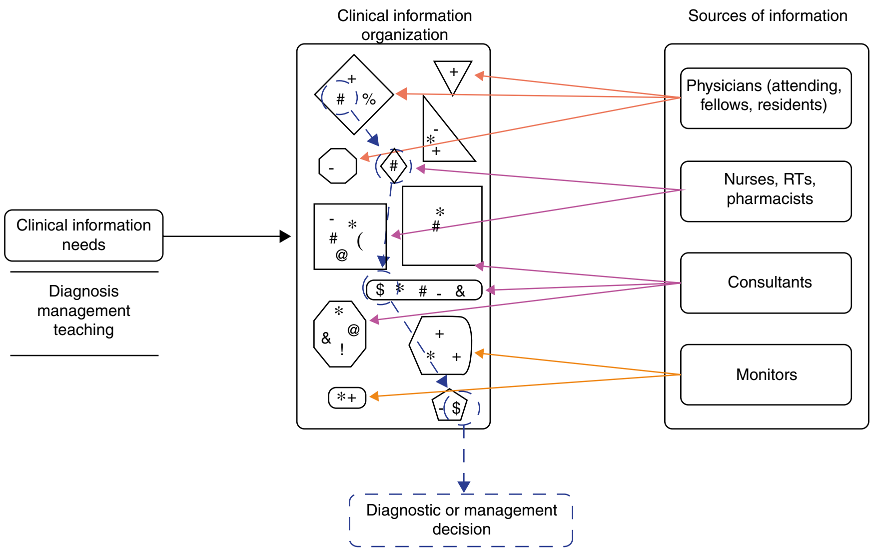

Fig. 18.1 Information sources and their organization in critical care environments: the distributed nature of clinical information organization is shown in the *central box* and the *dotted lines* show the trace of the relevant information that is abstracted for a diagnostic decision

clinicians (both physicians, nurses and other healthcare professionals) [2–6] very little is known about the processes and mechanisms that underlie the clinicians' use of the information sources. Additionally, most of the prior work on information needs and use has been conducted in primary care settings.

The process of information seeking is likely to be significantly different in the highly information-intensive and collaborative environment of critical care, where clinicians are face the arduous task of finding the right information to complete their tasks in a timely manner. Additional challenges arise due to the significantly collaborative nature of critical care work that requires significant interaction between the clinicians to manage a smooth and efficient patient care process. For example, patient information is often added to a central patient record repository by different clinicians – attending physicians, residents, nurses and other support personnel. As a result, when a physician has to develop a concrete understanding of the patient's Fig. 18.1 shows how different clinicians incorporate information into a patient's chart and how they have to locate the relevant information for making diagnostic and management decisions (dotted lines show the trace of the relevant information that is abstracted for diagnosis decisions). As highlighted in Fig. 18.1, the distributed nature of information organization in critical care settings has significant effect on the process of information seeking including: (a) *increased patient diagnosis time* resulting from longer time for filtering and organizing information. This leads to inefficiencies in diagnosis and decision-making. (b) Additionally, it also increases the potential for the *loss of information* when the necessary information cannot be found in a timely manner, consequently, increasing the potential for errors, and (c) the presence of multiple sources of similar information results in *redundancy of* *available information* and also increases the need for the physician to constantly switch among these resources to find appropriate information for their needs. In this chapter, we investigate how such challenges manifest during clinical information seeking tasks for making patient diagnosis decisions in critical care.

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) 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.

Method

This section describes the setting, participants, data collection, and data analysis that were used for this study. A detailed description can be found in [7].

Setting and Participants

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" [8] MICU (medical intensive care unit) managed by intensivists. In the unit, both paper and electronic charts were simultaneously maintained and used for patient care documentation (See Table 18.1 for a description).

Eight (n = *8*) MICU physicians participated in the study (6 attending physicians, 1 third-year resident, 1 clinical fellow). 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.

Procedure

Participants were asked to walk through the steps needed to create a clinical summary reviewing the details from a single patient case using information from charts (electronic and paper), and interactions with other clinicians. Clinicians verbalized ("thought-aloud") the relevant information related to their actions [9]. For example, the participants demographics and history were described (e.g., "this is a 34-year old African American male with a history smoking related issues"). The participants also nominally mentioned the sources from which they gleaned the information (e.g., "on resident notes") and their rationale as to why the considered information was important. Verbal think aloud techniques are commonly used in biomedical informatics research (e.g., [10, 11]) and are powerful mechanisms for developing

Table 18.1 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, physical 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.

insights on human cognition and decision-making. At the end of their information seeking process, participants provided a clinical summary of the patient where they described the patient case followed by their assessment and plan for that patient. Each verbal report was audio recorded and then transcribed for further analysis.

Data Collection

All data collection sessions were conducted after morning rounds (late morning or early afternoon) between October and December of 2010. 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 3 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 collaborators ensured that the patient mix was similar across the 3 days.

Fig. 18.2 iPad application used for data collection

For each session, one researcher wrote down detailed notes regarding the physician actions, sources used, and clinical personnel they interacted with and all other task related activities. Simultaneously, the second researcher captured the duration of each action (or task) using an iPad application [12]. The application provided a simple touch-based mechanism to capture the duration of access of each source (e.g., resident note, see Fig. 18.2) 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. Verbalized transitions (e.g., "now I am going to look at the resident notes from today's rounds") assisted partially with the reconciliation across sources.

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. 18.3. The columns represent the type of information source (paper or electronic), information sub-source (e.g., resident note), time at which the source was accessed, the information category (e.g., history and physicals from resident note, based on categories provided in Table 18.1),

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. 18.3 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)

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 to organize information. 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.

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. 18.3, 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.

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_o

$$G_o = \frac{Total\ no.information\ units\ in\ sub\text{-}source}{Time\ spent\ on\ sub\text{-}source}$$

Here, the sub-source would include categories mentioned in Table 18.1 and an information unit was the clinically relevant information provided in the "information unit" column in Fig. 18.3. G_o 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

Table 18.2 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 [17]
Resident note	27	24	3	0	[24 * 1 + 3 * 0.5] = **25.5**	158	[25.5/27]/158 = 0.005

theorem [13–15]. 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 [1] or in Pirolli [16, 17]. 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* [18] 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 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* [18] 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 18.2.

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.

Structure of Medical Knowledge

The patient-related detail (see "Information Unit" column in Fig. 18.3) was categorized using the medical knowledge framework [19, 20]. 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 [21], diagnostic reasoning [22, 23], nature of clinical expertise [23] and clinical comprehension [24]. 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., [25]), 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 18.3.

All transcripts were coded using the knowledge categories provided in Table 18.3. 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

Table 18.3 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 (Ventillation-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

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.

Results

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., [26–28]), we found that information was distributed among 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 is 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.

The distributed nature of information led to a fragmented process of information seeking, aggregation and organization. Physicians differed in the order in which they utilized the various information sources. While, most physicians started their diagnosis process with the paper chart others depended heavily on the electronic charts for patient related information. While the use of electronic records and patient interaction were an integral part of all physicians information seeking process, the use of paper charts and interactions with other clinicians depended on several factors including complexity of the patient case, familiarity with the patient case, physician's personal preferences, and the patient LOS in the MICU. Based on our analysis, we found that the information seeking process to be *exploratory*, *cumulative*, and *iterative* (this is further discussed in the section "Discussion"). The information sources and a preliminary framework of physician information seeking during clinical decision-making tasks is shown in Fig. 18.4. The figure shows three separate sources (and modalities) of information that differ in the nature, type and structure of available information. The arrows between the sources shows the iterative nature of the utilization of information for clinical decision making process.

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.

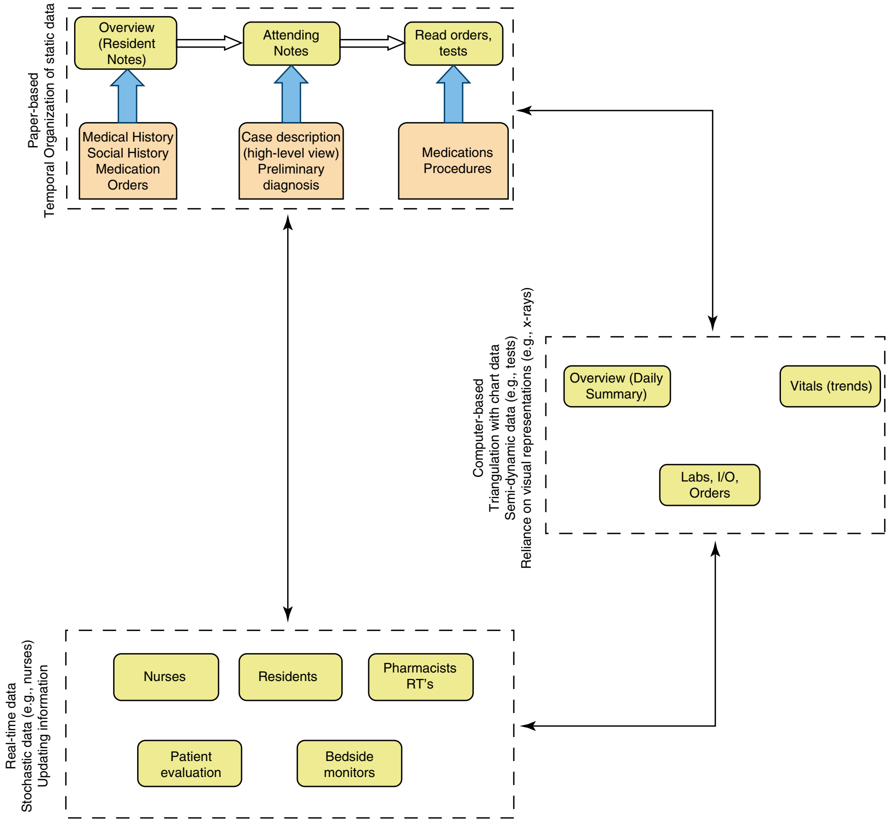

Fig. 18.4 Sources and utilization of information resources

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.

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,

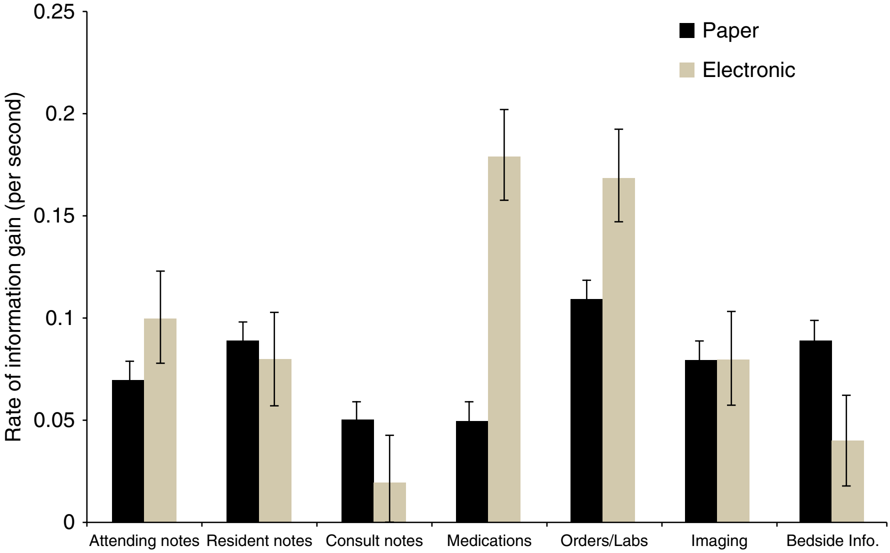

Fig. 18.5 Relative rate of information gain (i.e., information gain/time spent) of the various information sources in the MICU. The x-axis represents the various sub-sources of information and y-axis represents the information gained

medications and orders/labs was significantly higher in an electronic format. The differences in the other sub-sources were marginal (or non-existent). Figure 18.5 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 [29]. For example, tables and graphs aid in easier interpretation and comprehension of information.

Optimal Rate of Information Gain

From our data, we computed the optimal time spent on a resource that resulted in the highest rate of information gain. This was computed by aggregating the rate of gain of information for each source per document plotting against time (see Fig. 18.6) on a log-log scale.

In the figure, the light-shaded line (marked "data line") shows the rate of gain of information. The dark-shaded line (marked "trend line") shows the best-fit trend line based on the available data. The slope of the trend line gives the optimal time spent within a data source with maximum information gain. The *x*-axis and *y*-axis

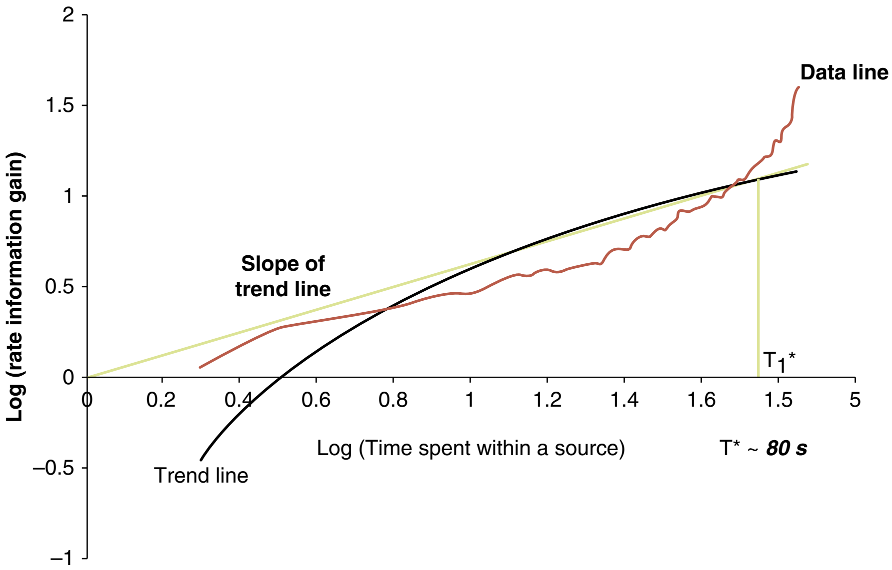

Fig. 18.6 Log-log plot of rate of information gain versus time spent within the resource. The graph shows the "data line", the rate of gain of information across sources (with increasing time), the "trend line", which represents the best fit of the data, and the "slope of the trend line"

represent the time spent on a resource and rate of information gain respectively on a log-scale. From our data, this optimal time spent (t^*) to be around 80 s.

We found that physicians spent around 80 s predominantly on orders/labs (electronic), pre-ICU notes (paper), and bedside information/flow sheets (paper). In other words, the optimal time spent for highest information gain, was achieved for those sources that had high rate of information gain (see Fig. 18.5 for sources that had the highest rate of information gain). The optimal time spent (t*) was based on a small data set for specific disease conditions and using the format at our study site. We also found that physicians spend significantly more time on resident notes (mean =240 s) and attending notes with lesser rate of information gain (see Fig. 18.6).

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. 18.7. 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

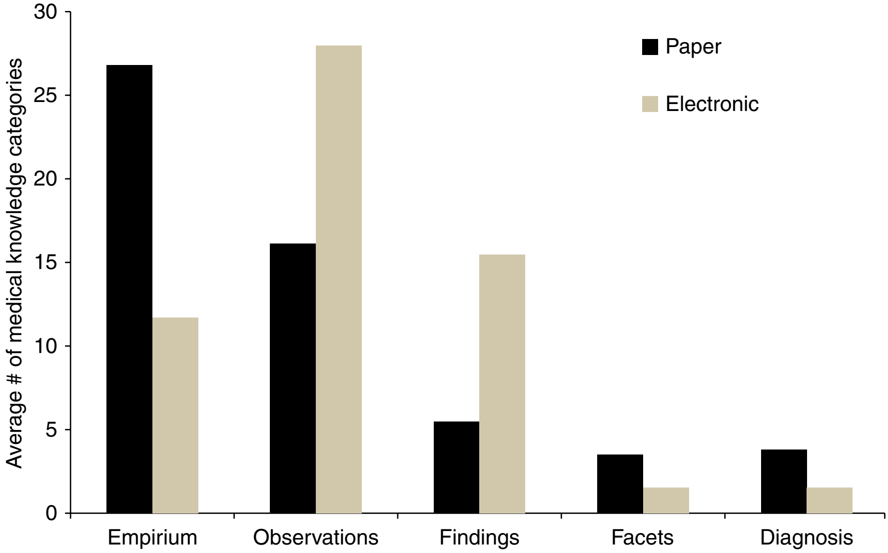

Fig. 18.7 Average number of medical knowledge categories in paper and electronic records

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.

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 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.

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 markups. 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 [17, 30] 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. [31] 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 towards complete electronic adoption by 2014, the importance of enriching aspects of Electronic Health Record (EHR) use is very important.

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 [10, 20].

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., [21]). 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 [32].

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 [33].

Based on our evaluation and analysis, we found that the information seeking process is *exploratory*, *cumulative*, and *iterative*. During information seeking process physicians had to constantly *find* and *re-find* information from multiple sources to confirm or invalidate a hypothesis. In particular, they depended on certain sources for certain types of information and this resulted in physicians requiring to return to previously encountered information to confirm the information that was previously gathered. 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 constant iterative back-and-forth switching between multiple sources.

As described elsewhere [10, 34, 35], information filtering occurs during diagnostic reasoning and requires significant cognitive effort from the physician. The distributed nature of information in critical care created extra information load: both in terms of finding the appropriate information and in using the appropriate resource to find the right information. Hence, even with the availability of structured electronic records, most physicians preferred to switch between the resources to find information necessary for making their decisions. Such switching added extra time and steps to their tasks, consequently, decreasing the efficiency of their work.

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.

Directions for Future Work

In this chapter, we discussed an information-theoretic approach to evaluating information seeking practices among clinicians. As previously discussed, the process of information seeking in clinical environments is not well understood – an understanding that can potentially have significant effect on clinical and management outcomes. For example, differences that exist in the information seeking practices of experts (e.g., attending physicians) and novices (e.g., interns or medical students) can have significant consequences for a number of things including the design of health information technology that supports clinicians' activities, cognitive load during work activities, and the management of clinical workflow.

In an ongoing exploratory study, we investigated the differences in processes and strategies of information seeking between residents and affiliate providers (nurse practitioners [NPs] and physician assistants [PAs]). Initial results from the study showed fundamental differences in the information seeking strategies of residents and affiliates: residents predominantly utilized a *patient-based* approach of aggregating all relevant information for one patient at a time. In contrast, the affiliates used a *source-based* approach in which similar (or equivalent) information was aggregated for multiple patients at a time (e.g., x-rays for all patients).

Similar studies that explore the information seeking strategies of clinicians during various critical clinical activities (e.g., handoffs) can provide significant insights are multiple levels: understand the information needs, characterize the challenges faced during information seeking, the tools (or technology) that can potentially support these activities, potential for errors or missed information and other socio-technical issues.

Discussion Questions

1. What are some of challenges that clinicians face for information gathering in critical care environments? How can we mitigate the effects of such challenges?

2. What role does health information technology play in mitigating the information overload challenges? What technological support can aid the streamlining of the information seeking in clinical workflows?
3. The use of electronic health records (EHR) has been shown to affect clinical reasoning relative to paper charts. How does the use of EHR as a primary data gathering (information seeking) tool affect the reasoning process? Are there any detrimental effects?

References

1. Pirolli P, Card S. Information foraging. Psychol Rev. 1999;106:643–75.
2. Covell DG, Uman GC, Manning PR. Information needs in office practice. Ann Intern Med. 1985;103(4):596–9.
3. Gorman PN, Helfand M. Information seeking in primary care: how physicians choose which clinical questions to pursue and which to leave unanswered. Med Decis Making. 1995;15(2): 113–9.
4. Cogdill KW, Friedman CP, Jenkins CG, Mays BE, Sharp MC. Information needs and information seeking in community medical education. Acad Med. 2000;75:484–6.
5. Davies K, Harrison J. The information-seeking behaviour of doctors: a review of the evidence. Health Info Libr J. 2007;24(2):78–94.
6. Green ML, Ciampi MA, Ellis PJ. Residents' medical information needs in clinic: are they being met? Am J Med. 2000;109:218–23.
7. Kannampallil T.G, Franklin A, Mishra R, Cohen T, Almoosa KF, Patel VL. Understanding the Nature of Information Seeking Behavior in Critical Care: Implications for the Design of Health Information Technology. Artif Intell Med. 2013;57(1):21–29.
8. Safar P, Grenvik A. Organization and physician education in critical care medicine. Anesthesiology. 1977;47(2):82–95.
9. Ericsson KA, Simon HA. Verbal protocol analysis: verbal reports as data. Cambridge: MIT Press; 1993.
10. 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. J Biomed Inform. 2009;42(1):176–97.
11. Patel VL, Zhang J, Yoskowitz NA, Green R, Sayan OR. Translational cognition for decision support in critical care environments: a review. J Biomed Inform. 2008;41(3):413–31. PubMed PMID: 18343731. Pubmed Central PMCID: 2459228. Epub 2008/03/18. eng.
12. Li Z, Robinson DJ, Zhang J. UObserve: a mobile app for the study of emergency department workflow. Annals of Emergency Medicine 2010;56(3): S121.
13. Charnov EL. Optimal foraging: the marginal value theorem. Theor Popul Biol. 1976;9:129–36.
14. Stephens DW, Charnov EL. Optimal foraging: some simple stochastic models. Behav Ecol Sociobiol. 1982;10:251–63.
15. Stephens DW, Krebs JR. Foraging theory. Princeton: Princeton University Press; 1986.
16. Pirolli P. Rational analyses of information foraging on the web. Cognit Sci. 2005;29(3):343–73.
17. Pirolli P. Information foraging: a theory of adaptive interaction with information. New York: Oxford University Press; 2007.
18. 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.
19. 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: MIT Press; 1989. p. 211–55.

20. Patel VL, Kaufman DR. Medical informatics and the science of cognition. J Am Med Inform Assoc. 1998;5(6):493–502. PubMed PMID: 9824797. Pubmed Central PMCID: 61330. Epub 1998/11/24. eng.
21. 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. San Diego: Academic; 1994. p. 187–252.
22. Patel VL, Kaufman DR, Arocha JF. Emerging paradigms of cognition in medical decision-making. J Biomed Inform. 2002;35(1):52–75. PubMed PMID: 12415726. Epub 2002/11/06. eng.
23. Patel VL, Groen GJ, Scott HS. Biomedical knowledge in explanations of clinical problems by medical students. Med Educ. 1988;22(5):398–406.
24. Patel VL, Kushniruk AW, Yang S, Yale JF. Impact of a computerized patient record system on medical data collection, organization and reasoning. J Am Med Inform Assoc. 2000;7(6): 569–85.
25. Arocha JF, Wang D, Patel VL. Identifying reasoning strategies in medical decision making: a methodological guide. J Biomed Inform. 2005;38(2):154–71.
26. 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. Int J Med Inform. 2007;76(11–12):801–11. PubMed PMID: 17059892. Epub 2006/10/25. eng.
27. Malhotra S, Jordan D, Shortliffe E, Patel VL. Workflow modeling in critical care: piecing together your own puzzle. J Biomed Inform. 2007;40:81–92.
28. Patel VL, Cohen T. New perspectives on error in critical care. Curr Opin Crit Care. 2008; 14(4):456–9.
29. Zhang J, Norman DA. Representations in distributed cognitive tasks. Cognit Sci. 1994; 18(1):87–122.
30. Sandstrom PE. Scholarly communication as a socioecological system. Scientometrics. 2001; 51(3):573–605.
31. Sharda P, Das AK, Cohen T, Patel VL. Customizing clinical narratives for the electronic medical record interface using cognitive methods. Int J Med Inform. 2006;75(5):346–68.
32. Patel VL, Groen GJ. Real versus artificial expertise: the development of cognitive models of clinical reasoning. In: Stefanelli M, Hasman A, Fieschi M, Talmon J, editors. Proceedings of the third conference on AI in medicine, Lecture notes in medical informatics (44). Maastricht: Springer; 1991. p. 25–37.
33. Patel VL, Shortliffe EH, Stefanelli M, Szolovits P, Berthold MR, Bellazzi R, et al. The coming of age of artificial intelligence in medicine. Artif Intell Med. 2009;46:5–17.
34. Patel VL, Arocha JF, Kaufman DR. Diagnostic reasoning and expertise. In: Medin D, editor. The psychology of learning and motivation: advances in research and theory, vol. 31. San Diego: Academic; 1994. p. 137–252.
35. Evans D, Gadd C. Managing coherence and context in medical problem-solving discourse. In: Cognitive science in medicine: biomedical modeling. Cambridge: MIT Press; 1989. p. 45.