Context Sensitive Health Informatics: Many Places, Many Users, Many Contexts, Many Uses
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A Sequential Data Analysis Approach to Electronic Health Record Workflow

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Abstract. Failure to understand clinical workflow across electronic health record (EHR) tasks is a significant contributor to usability problems. In this paper, we employed sequential data analysis methods with the aim of characterizing patterns of 5 clinicians' information-gathering across 66 patients. Two analyses were conducted. The first one characterized the most common sequential patterns as reflected in the screen transitions. The second analysis was designed to mine and quantify the frequency of sequence occurrence. We observed 27 screen-transition patterns that were employed from 2 to 7 times. Documents/Images and Intake/ Output screens were viewed for nearly all patients indicating the importance of these information sources. In some cases, they were viewed more than once which may show that users are following inefficient patterns in the information gathering process. New quantitative methods of analysis as applied to interaction data can yield critical insights in robust designs that better support clinical workflow.

Keywords. Electronic health records, usability, sequential pattern analysis, process mining

1. Introduction

The development and implementation of clinical information systems continue to proliferate at a rapid pace. Although Electronic Health Record systems (EHR) have the potential to transform patient care and clinical communication, they have thus far fallen well short of that objective. Studies have documented user dissatisfaction with current systems and usability problems [1]. In addition, poorly designed interfaces have been shown to compromise patient safety and are a known source of medical errors [1]. Clinicians in hospital settings spend much time on documentation. The absence of a focus on system usability and on understanding patterns of workflow is major impediment to adoption and widespread use.

Usability studies typically employ methods such as surveys, expert inspections and usability testing experiments [2]. Although these methods are informative, they involve a reliance on subjective judgment, may lack reliability and do not provide a sufficently rich window into the clinical workflow process. Zheng and colleagues [3] introduced *computational ethnography*, an emerging class of techniques for conducting Human-Computer Interaction (HCI) studies in healthcare. They leverage automated methods for collecting *in situ* data which captures users' actual behaviors using a system or a device in real-world settings. Sequential pattern analysis employ log files to search for recurring patterns within a large number of event sequences [4]. The analysis can be used effectively in concert with other forms of data such as ethnography or video-capture of end-users performing clinical tasks.

Zheng et al [2] investigated users interaction with an EHR by uncovering hidden navigational patterns in EHR logfile data. Towards that end, they employed sequential pattern analysis to identify recurring feature access in a particular chronological sequence. Various patterns were seen to be at variance from optimal pathways as suggested by designers and individuals in clinical management. A similar study was conducted by Kannampallil et al [5]. They leveraged workflow logfile data to compare the information-seeking strategies of clinicians in critical care settings. Specifically, they characterized how distributed information within the settings was searched, retrieved and used during clinical workflow. They found that residents predominantly used a "patient-based" information-seeking strategy in which all information was collected for one patient at a time. On the other hand, nurse practitioners and physician assistants employed a "source-based" strategy in which similar information was aggregated for all patients at a time (e.g., vital signs). They concluded that there are costs (e.g. effort, time and cognitive load) associated with particular strategies.In addition, different interface designs are likely to better support particular strategies. For example, a source-based approach may be better supported by enriched external representations that facilitate visualization and rapid aggregation of patient data.

The objective of this research is to analyze sequential patterns of clinicians access of EHR screens in gathering patient information prior to morning rounds. This study is part of an active practice redesign effort at the Mayo Clinic that has been shown to enhance quality of care through improved health information technologies. A focal point of the research is to understand clinical workflow at varying levels of abstraction (e.g., individuals to teams) and organization (clinical departments and divisions). We studied clinicians as they engage in a range of tasks from preparing progress reports to order entry. A particular focus of the work presented in this paper is EHR workflow.

2. Materials and Methods

2.1. Clinical Setting

The study was conducted in the Colon and Rectal Surgery (CRS) Division at Mayo Clinic, Rochester, MN, an academic tertiary healthcare center equipped with a comprehensive EHR. Access to patient data is achieved through a customized interface, Synthesis. In the unit, patients are cared for by nurses, hospitalists, residents, fellows, and surgeons. We observed three hospitalists, a physician assistant (H1) and two nurse practitioners (H2 and H3), who both fill the same hospitalist (H) role in the unit, and two residents, a 2nd year (R1) and 4th year (R2). Hospitalists responsibilities include, but are not limited to, order entry, documentation, scheduling follow-up appointments, review and reconciling medications. H1, H2 and H3 were experienced users of the system and routinely performed the tasks we observed. R1 and R2 were doing a rotation in the unit and were less experienced users of the system in the CRS division. The study was reviewed by the Mayo Clinic IRB and judged to be exempt.

2.2. Data Collection and Analysis

The data was collected as the clinicians were completing pre-rounds information gathering. The pre-rounds data gathering task occurs close to the start of the 12-hour shift, approximately 6:00 am. Hospitalists and residents round together immediately afterwards. The goals of the task are to access the most recent information on patients' medical status, review care plans, and to anticipate patient needs for the current day.

Clinicians were observed in the clinical setting, performing pre-rounds information gathering in the context of their routine workflow. The participants verbalized their thoughts and the sessions were recorded using Morae™ video-analytic software. The software provides a screen capture and a set of analytics (e.g., mouse clicks). There were a total of 66 patients including 9 from H1, 21 from H2, 16 from H3, 12 from R1, and 8 from R2. Only two patients overlapped between H2 and H3. Morae™ was used to parse the file, note time and code screen transitions. The start time of the subsequent screen was used as the end time of the previous screen. Screen transitions are defined by a significant change in the display view that requires the participant to reorient themselves to a different set of data. Screen transitions included a transition between applications, transition between tabs or views within an application. Most of the screens corresponded to components of the EHR including Documents and Images, Intake-Output, Labs, Vital Signs, Patient Navigation Panel and Summary.

We conducted two sequential data analyses to investigate patterns of information-seeking. The analyses were conducted using PROM, a free process-mining workbench used for business process management, and most recently in healthcare [6], in view to improve productivity[7]. The input of PROM is a set of event logs (in our case the output from Morae™), which can be processed, analyzed, and visualized. For this study, we used 2 plug-ins for PROM 5.2 including the *Frequency Abstraction Miner* plug-in [7] to characterize the most common sequential patterns as reflected in the screen transitions across 5 subjects and 66 patients. The plug-in uses significance/correlation metrics to iteratively simplify the process model at a desired level of abstraction (in our case, 0.100). The importance of events and transition is evaluated by frequency, i.e. more frequently visited screens are considered more important. We used the *Performance Sequence Diagram Analysis* plug-in to mine and quantify the frequency of sequence occurrence. In pattern diagrams, identical sequences are represented by one pattern. We defined criteria to distinguish sequences as follows: a sequence of screen transition $S1\text{-}S2\text{-}S3\ldots Sn$ is similar to a sequence of transitions $T1\text{-}T2\text{-}T3\ldots Tn$ if and only if for all $0<i<n+1$: $Si=Ti$ independently of the temporal constraints (e.g., duration) of Si and Ti.

3. Results

The results from the *Frequency Abstraction Miner* documented recurrent patterns of transitions. For 66 patients, three screens were viewed more than 66 times: Navigation, Documents/Images, and Intake/Output. The most frequent screen transition pattern Navigation to Documents/Images to Intake/Output to End (**Pattern 1**: N-D-I-End) occurred nine times. The next two most frequent patterns occurred five times each including Navigation to Documents/Images to Intake/Output to Vital Signs to Labs to End (**Pattern 2**: N-D-I-V-L-End), and Navigation to Summary to Labs to Vital Signs to Intake/Output to Documents/Images to End (**Pattern 3**: N-S-L-V-I-D-End).

Upon selecting a patient in Navigation, the user is immediately transferred to a screen in the newly opened patient's chart. The transitions leading from Navigation to Documents/Images and Navigation to Summary are among the most probable, 0.451 and 0.378 respectively, because the observed users have one of these two screens set as the default opening screen. H2 and H3 have Documents/Images screen displayed when opening a patient's chart and never transition to the Summary screen. H1, R1 and R2 have the Summary display set as default screen when opening a patient's chart. In fact, the Summary screen has 51 occurrences across 29 patients because R1 visits the Summary display 2.75 times per patient (range 1 – 5). The Navigation Panel was accessed for all patients because it is the location of the patient list and the search field for a user to access a patient chart.

Documents/Images and Intake/Output screens were viewed for nearly all patients suggesting the importance of these displays as information sources. The fact that they were viewed more than once for some patients may suggest that users are following inefficient patterns in the information gathering task. Participants may navigate to these screens more than once for some patients because data gathered from another screen or from the paper handoff document used for note taking provokes them to return to a previously viewed screen.

Table 1 indicates the number of times each pattern was employed by the clinicians. The most frequent screen sequence (Pattern 1) was followed by H2 five times and by H3 four times. The next three most frequent screen sequences were each followed by one provider—H1 five times (Pattern 2), H2 five times (Pattern 3) and H3 three times (Pattern 4). Of the six patterns that had two repetitions each (Patterns 5-10), three were followed by the same clinician (H2 followed Patterns 7 and 10; R2 followed Pattern 8). The remaining 32 patients elicited a pattern that appeared only once (Patterns 11-42).

Table 1. Frequency of Pattern Type by User

User/Pattern	H1	H2	H3	R1	R2	Totals
1	0	5	4	0	0	9
2	5	0	0	0	0	5
3	0	5	0	0	0	5
4	0	0	3	0	0	3
5	1	0	0	0	1	2
6	0	0	0	1	1	2
7	0	2	0	0	0	2
8	0	0	0	0	2	2
9	0	1	1	0	0	2
10	0	2	0	0	0	2
11-42	3	6	8	11	4	32
Total	9	21	16	12	8	66

Table 2. Human-Computer Interaction Measures by Pattern of Transitions

Patterns	Screen Transitions	Mouse Clicks	Duration
1	3.3 (2.7)	7.7 (7.3)	63.0 (40.5)
2	5.0 (0.0)	11.4 (4.5)	75.1 (17.3)
3	4.0 (0.0)	10.6 (6.6)	59.6 (39.3)
4	4.7 (0.6)	11.7 (1.5)	86.4 (14.7)
5	4.0 (0.0)	7.5 (0.7)	84.5 (24.8)
6	2.0 (0.0)	7.0 (5.6)	55.5 (31.8)
7	2.5 (0.7)	4.5 (0.7)	39.4 (14.4)
8	9.5 (0.7)	15.0 (1.4)	125.0 (8.5)
9	7.5 (3.5)	19.0 (12.7)	145.2 (49.3)
10	3.0 (0.0)	6.0 (1.4)	48.8 (20.9)

Table 2 presents an analysis of the patterns according to HCI measures including screen transitions, mouse clicks and duration. The objective of this analysis is to characterize the difference in complexity for each pattern. The first pattern, employed by 2 different hospitalists and for a total of 9 patients, is among the least complex involving an average of only 3.3 screen transitions, 8 mouse clicks and 63 seconds to complete. On the other hand, pattern 2 involved 5 screen transitions, 11 mouse clicks and 75 seconds to complete. This pattern, employed by a single hospitalist for 5 patients, involved sequential transitions from left to right corresponding to the order of tabs along the top of the screen. Although some of the complexity can be accounted for by the interface, others may reflect provider efficiency and clinical case complexity.

4. Discussion

Computational ethnography offers a new suite of quantitative tools and methods for studying interactive behavior [3]. Log-file analysis is increasingly being used as means to understand user behavior in a broad range of contexts. For example, Hripcsak et al employed audit logs to measure the amount of time clinicians spend authoring or reviewing EHR documentation [8]. Zhang employed audit logs to study improper access to patient records potentially resulting in violations of privacy protocols [9]. In this study, we conducted a sequential data analysis of clinician performing an information-gathering task. We employed a process mining tool (PROM 5.2) frequently used for business [10] and healthcare process management [6]. However, there have been only a few studies focused on sequential analysis of screen transition patterns. The results of this study further suggest that this is a promising method for understanding EHR workflow and for drawing design implications.

The study documented 3 sequential patterns of screen transitions that accounted for a total of 19/66 (29%) of patients, 7 additional patterns accounted for 15 patients (23%) and the patterns for the remaining 32 patients were entirely different from all others. Although we are just beginning to scrutinize the costs (e.g., time, cognitive load) associated with each interaction pattern, we can speculate that some patterns are more efficient than others. We did observe regressions in which a clinician made one or more return visits to the same screen. In addition, it is possible that certain patterns may deviate from clinical pathways. However, we cannot answer that question at this point, although the converging sources of data available to us (including a video record of all interactions) should yield insights into this important problem.

In this study, all interactions followed a patient-based approach rather than source-based approach found by Kannampallil [5]. That may be a function of the different systems or workflows. For example, it may be more costly for users in this study to go back and forth between patients. It could also be a matter of convention or clinical protocol that guided information gathering. These authors make a compelling case that different interfaces and external representations (e.g., visualizations) may best support the different patterns of interaction.

In this data set, we have several sources of sequential data including a think-aloud protocol, video-recordings of all interactions and now the process mining data involving screen transitions. We endeavored to correlate transitions patterns with various HCI measures. We observed that a transition resulted in 2 to 2.5 mouse clicks. The durations of interaction per patient were highly variable and could be associated with factors like interruptions and clinical case complexity.

We are currently exploring the use of this method for documentation tasks including progress reports and discharge summaries. It is likely that patterns of interaction will be quite different from the information-gathering task employed in this study. It is our conjecture, that the mining of interaction behaviors across a range of tasks can yield a set of desiderata for clinical information systems design. This preliminary study employed a small data set of 66 patients and is best viewed as exploratory research. However, there are also advantages to this approach. The primary one is the ability to correlate process mining data with observed patterns of interaction. For example, if we notice aberrant patterns, we can explore the problem in considerable depth via the use of video and think-aloud protocols. This could potentially lead us to isolate the causes of such problems.

5. Conclusion

The last decade has witnessed extraordinary growth in the implementation and adoption of clinical information systems across hospital and ambulatory care settings. There is also ample evidence to suggest that it has been a bumpy ride for both implementers and end users. The quantitative and qualitative tools available to researchers and practitioners have developed immeasurably in recent years and were used in this work to characterize patterns of information-gathering that may vary in efficiency and in adherence to guidelines. There are techniques, included the process mining method explained here, that could potentially help us to discover, analyze and visualize records of HCI that could lead to improved EHR designs. A better understanding of clinical workflow is essential to support the next generation of EHR design.

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