An Interface-Driven Analysis of User Behavior of an Electronic Health Records System

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ABSTRACT

Objective: To study user behavior of an electronic health records (EHR) system by discovering sequential usage patterns in clinicians' day-to-day interaction with the system's software user interface.

Design: The EHR was modified to log comprehensive interaction details as clinicians navigate through its interface to perform different clinical tasks. The interaction details, comprising time-stamped clickstream events, allow how the system was actually used in naturalistic settings to be replayed.

Methods: Sequential pattern analysis and a first-order Markov chain model were used to discover recurring patterns in the recorded EHR interface usage.

Results: Out of 17 main features provided in the EHR, sequential pattern analysis discovered 3 *bundled* capabilities utilizing 6 of these features: "Assessment & Plan" $\rightleftharpoons$ "Diagnosis", "Order" $\rightleftharpoons$ "Medication", and "Order" $\rightleftharpoons$ "Laboratory Test". Clinicians often used these features together, and frequently switched between them back and forth. The Markov chain analysis revealed a *global navigational pathway*, indicating a preferred order in which different EHR features were sequentially accessed. "History of Present Illness" $\Rightarrow$ "Social History" $\Rightarrow$ "Assessment & Plan" ... is found to the favorite pathway traversed by many clinicians, along with several other frequent routes.

Conclusions: Clinicians demonstrated consistent behaviors in interacting with the EHR, some of which were not anticipated by the designers of the system or the clinic management. Awareness of such behaviors would inform a more effective EHR design, help clinicians standardize day-to-day clinical practice through consistent interaction with EHRs, and anticipate some unintended consequences of IT use related to software user interface design and workflow integration.

I. INTRODUCTION

Practice of medicine demands complex processing of large amounts of data and information, usually at the point of care and during busy practice hours. The increasing availability of electronic systems in healthcare has provided an unprecedented advantage of storing and retrieving patient data more effectively. However, the true value of these systems cannot be achieved unless they (1) present data, information, and knowledge to the right people, in the right format, and in the right sequence; and (2) allow time-sensitive tasks to be efficiently conducted, usually in a highly cooperative environment by a team of healthcare workers. An optimized software user interface (UI) design and a proper application flow (AF) alignment, therefore, are of vital importance. An intuitive, appealing UI also offers superior use experience, which is the key for any technological innovations to prevail.

Unfortunately, lack of effective, elegant user interface and/or finely tuned application flow has been a major impediment to the widespread adoption and routine use of health IT systems [1, 2]. Poorly designed UI and AP, in addition to problematic implementation processes, are also associated with unintended, negative consequences of IT use such as decreased time efficiency, increased threat to patient safety, and jeopardized quality of care [3–8]. Consequently, health IT systems fail to fulfill their promises, users are dissatisfied, costs and tensions escalate, and often systems are abandoned [9, 10].

Despite these facts, many health IT systems are still created *ad hoc*, with little systematic consideration for users, tasks, and environments [11]. Further, healthcare practice often results in users trained to adapt to poorly designed technology, rather than designing technology that is better-aligned to users' cognitive capacities, job characteristics, and the clinical workflow [2]. It is evident that in addition to outcomes-based evaluations, health informatics research should also focus on uncovering the cognitive, behavioral, and social roots that would help explain the observed outcomes, in particular, find out what may have caused health IT systems to fail [12–14].

Human-centered computing has been increasingly recognized as an important means to address the gap between anticipated outcomes of health IT and the increasing yet still limited impact that has been achieved. For example, Kushniruk and Patel (2004) proposed to use methods in cognitive and usability engineering to improve the usability of clinical information systems [14]; Johnson, Johnson & Zhang (2005) introduced a user-centered framework for guiding the redesign process of healthcare software user interfaces [11]; and Harrison, Koppel & Bar-Lev (2007) presented an interactive socio-technical analysis model for studying socio-technical issues associated with introducing IT in healthcare [15]. Usability studies, many of which instantiate the models and frameworks above, have been conducted to examine the designs of a wide range of healthcare technologies: from electronic health records systems [16–18] to computerized physician order entry systems [19] to emergency room medical devices [20–22]. Results of these studies not only illustrate the value of applying human-centered approaches to designing more effective healthcare IT systems, but also indicate the significant margin for improvement of the existing systems and the way they were being built.

Some of these studies have focused on achieving a 'perfect' design before a system is developed and deployed. Unfortunately, this approach is not feasible for studying EHRs given the current dominance of off-the-shelf commercial products in the EHR marketplace [23]. On the other hand, post-implementation usability research usually employs study designs such as ethnographic observations, expert inspections, simulated experiments, and satisfaction surveys. Some of these study designs can be difficult and expensive to conduct (e.g., video taping computer use sessions to reveal clinicians' cognitive walkthrough), or are subject to unreliabilities in users' self-reported data caused by multiple factors such as positive illusions and cognitive consistency. In addition, subjects participating in ethnographic observations and simulated experiments may demonstrate altered behavior due to the Hawthorne effect.

In this paper, we demonstrate a novel approach for studying user behavior and usability issues of a deployed electronic health records system. Non-intrusive data collection was conducted using the system's transaction database, which stores the usage of the EHR generated in naturalistic encounters with real patients. For research purposes, the EHR also annexed an add-on UI tracking mechanism that captures certain transitory UI events such as mouse clicks to expand or collapse a tree view. To analyze this interaction data, we use (1) sequential pattern analysis (SPA), which searches for segments of consecutive feature accesses recurring across patient encounters; (2) a within-session SPA, which computes the likelihood of a feature or a combination of features being re-accessed within an encounter; and (3) a first-order Markov chain model, which reveals the navigational pathway via which different EHR features are sequentially accessed. The objective of these analyses is to uncover hidden patterns in clinicians' interaction within the EHR, thus helps detect unanticipated behaviors in clinicians' day-to-day clinical practice or deficiencies in the system's UI and AF design.

In the next section, we present previous findings from evaluating an earlier implementation of the EHR. The results revealed several UI and AF usability issues, based on which the system was reengineered, redeployed, and reevaluated. Study design and analytical methods are presented in Section 3. Results are presented and discussed in Section 4 and Section 5, followed by some concluding remarks.

II. BACKGROUND

Over the past a few years, the research team has been working with practitioners at an urban teaching hospital to create a clinical decision-support system to enhance internal medicine residency training. This system, called Clinical Reminder System (CRS), is designed to manage a clinic's routine operation, facilitate clinical documentation *during* patient encounters, and generate clinician directed, point-of-care reminders using evidence-based clinical practice guidelines. An increased emphasis on patient data management as a prelude to reminder generation has led CRS to evolve over time into a standalone, light-weight EHR application. Comprehensive patient data including patient descriptors, symptoms, and orders are captured in the system, in addition to live or batched electronic feed of billing, registration, and laboratory test results data from/to other hospital information systems.

In February 2002, the first version of CRS (shown in Figure 1) was introduced to an ambulatory primary care clinic at the hospital. This clinic serves as a rotation site for the hospital's internal medicine residency training program. Clinicians' interaction with the system was facilitated via desktop computers installed in every examination room in the clinic. In a qualitative study that evaluated this earlier implementation, several negative themes were revealed in regard to clinicians' reaction to the use of the system in their clinical practice, including a salient complaint about "lack of guidance in the application's workflow" [24, 25]. This theme pointed to possible deficiencies in the system's UI and AF design, based on which a reengineering effort was initiated.

In redesigning CRS, the research team adhered strictly to the participatory design method, by working closely with attending physicians, lead residents, nurses, and clinic staff to collaboratively renovate the system's UI and AF elements [26]. The reengineering took one and half years to complete. Various enhancements were made, including a fully web-enabled interface, a more intuitive UI layout, and improved functionalities to support the clinic's resident training. This system reengineering effort thus incorporated the lessons learnt from the prior implementation combined with a better knowledge of end users' routine practice requirements. The current study evaluates these design assumptions and choices using data from subsequent daily usage of the system deployed anew in the same clinic.

III. DESIGN

A. Study Setting and Participants

The reengineered version of CRS was deployed in the same clinic in June 2005. Figure 2 shows its new software user interface. One-on-one hands-on training was provided in the subsequent month.

In this study, we analyze and report 10-month EHR usage data collected from October 1, 2005 to August 1, 2006. Forty residents were registered in the system during this time period, 10 of whom were excluded from the study because they logged usage in fewer than 5 patient encounters. Their limited exposure to the system was deemed inadequate to allow mature usage behaviors to be revealed. Since the attending physicians in the clinic only used the system to review and approve the residents' work, their usage was not considered.

Because the provisioning of point-of-care reminders has been known to significantly interrupt the clinic's workflow [25], we chose not to activate the reminding functionality when this study was conducted. Hence the usage reported in this paper includes only the usage of the system's EHR features. There were 17 such features considered necessary by clinicians during the design of the EHR for the targeted outpatient environment, labeled with distinct letter symbols as shown in Table 1. A symbol is usually the first letter of a feature unless there is a conflict, for example A represents "**A**ssessment & Plan", G represents "Aller**G**ies", M represents "**M**edication", E represents "Medication Side **E**ffects", and so forth. Figure 3 shows the layout of the system's reengineered UI and onscreen position of each of these 17 features. Users may scroll up or down in the main workspace to navigate to other segments of the system, or use the function navigator menu provided to the left of the screen.

B. Methods

Event sequences discussed in this paper are constructed by encoding a series of EHR feature accesses according to the labeling schema above and ordering them based on their timestamps recorded. HMMXAD, for example, is an event sequence composed of 6 consecutive EHR feature accesses that occurred chronologically during a patient encounter: "History of Present Illness" (H) $\Rightarrow$ "Medication" (M) $\Rightarrow$ "Medication" (M) $\Rightarrow$ "Physical Examination" (X) $\Rightarrow$ "Assessment & Plan" (A) $\Rightarrow$ "Diagnosis" (D). Table 2 shows some sample usage data recorded in CRS and how the event sequences were constructed. Below we present three analytical methods used to analyze these event sequences.

1) Sequential pattern analysis

Sequential pattern analysis (SPA) discovers hidden and recurring patterns within a large number of event sequences [27]. It has applications in many areas such as predicting future merchandise purchase based on a customer's shopping history [27] and providing personalized web content based on an internet user's surfing record [28]. In this study, we use a simplified SPA algorithm to detect recurring segments of consecutive EHR access events. In other words, we use SPA to discover combinations of EHR features consecutively accessed, in the same sequential order, by many clinicians, and across many patient encounters.

Given a set of Y event sequences, let p denote a segment of sequence that is a subset of, or contained by, X event sequences. p is called a *sequential pattern* when its support $\frac{X}{Y}$ is larger than a pre-defined minimum threshold of support, Z. A sequential pattern that is not contained by any other patterns is called a *maximal pattern*. The goal of SPA is to discover all such maximal patterns. When Z is a constant for patterns of any given length, the most efficient search algorithm starts with computing the support for all sequences with 2 consecutive events. When a 2-event sequence does not satisfy the minimum support threshold Z, it is removed from further consideration; otherwise, it is retained as a candidate sequence to compute the support for subsequent larger length sequences. The algorithm stops when no larger length patterns can be found. The current candidate sequence is then chosen as a maximal pattern.

2) Analysis of within-session recurrence rates

Sequential pattern analysis searches for recurring segments across event sequences. It would also be interesting to determine if certain segments of events tend to have a high probability of repeating within the same sequence; in other words, if certain EHR features or combinations of EHR features have been used once, what is the likelihood that they will be used again within the same patient encounter? Collectively, the within-session analysis combined with the sequential pattern analysis would provide a better understanding of which EHR features tend to be 'glued' together, leading to useful UI design insights.

A variation of the SPA algorithm is used to compute the within-session recurrence rates of all sequential patterns identified by SPA. For example, the recurrence rate of a hypothetical pattern AD ("Assessment & Plan" ⇒ "Diagnosis") is calculated as the number of event sequences in which AD appears more than once divided by number of all event sequences that contain AD.

3) First-order Markov chain analysis

While the above analyses can identify usage patterns as recurring segments of events, they are not adequate to delineate the entire UI navigational pathway traversed by clinicians to perform different clinical tasks. We therefore introduce a first-order Markov chain model to uncover the *global navigational pathways*.

A Markov chain is a stochastic process with discrete states and transformations between states [29]. At specific time epochs, the system changes from one state to another. In the context of navigation in an EHR's user interface, a change of state occurs when a clinician switches from one feature to another. The Markov chain in this study thus comprises ordered steps of sequential EHR feature accesses. In a first-order Markov chain model, the probability of a future state depends solely on the immediately preceding state of the system, that is, the EHR feature that will be used next depends on the feature that is being used currently.

Let S_t denote the EHR feature being accessed at time t. A Markov chain model is expressed as a triple (Q, A, π), where $Q = q_1, q_2, \ldots, q_n$ is a set of possible system states (features); A denotes the matrix of transition probabilities, where $a_{ij} = P(S_t = q_j | S_{t-1} = q_i)$ is the probability that a clinician navigates from feature q_i to feature q_j; and π denotes the initial probability vector, where $\pi = P(S_0 = q_i)$ is the probability of observing q_i as the system's initial state, that is, the first EHR feature accessed.

In a first-order Markov chain model, the probability of observing $S(s_0, s_1, \ldots, s_T)$, where $s_0, s_1, \ldots, s_T$ denote the states (feature accesses) observed at time $t = 0, 1, \ldots, T$, is the product of the initial probability vector π and successive powers of the transition probability matrix A: $P(S_0 = s_0, S_1 = s_1, \ldots, S_T = s_T) = P(S_0 = s_0) \prod_{t=1}^{T} P(S_t = s_t | S_{t-1} = s_{t-1}) = \pi A^T$. The p_{ij}th entry in πA^T therefore designates the probability that feature q_i will be accessed in the jth step. In this study, the initial stationary probability vector π is obtained using a maximum-likelihood estimate as the fraction of event sequences starting in feature q_i. Similarly, the transition probability a_{ij} is a maximum-likelihood estimate of observing a state change (feature switch) from q_i to q_j, as a fraction of all possible transitions from q_i.

C. Data preparation

In the 10-month study period, 30 active residents recorded EHR usage in 973 unique patient encounters, yielding 973 constructed event sequences. The original event sequences contain segments of consecutively repeating events, for example, the MM segment in the HMMYAD sequence represents two successive medication orders. We decided to consolidated such consecutively repeating events into a single usage event, because this study is focused on discovering how clinicians navigate through the EHR's user interface to access *different* features: using the same feature successively multiple times does not incur the cognitive load of 'locating' another feature to work with on the computer screen, and is usually associated with specific patient care needs rather than the UI design of the system. The MM segment in HMMYAD, for example, was therefore consolidated into one single event M. The subsequent analyses were all conducted based on the consolidated event sequences.

IV. RESULTS

A. Frequency of feature accesses

The overall frequency of accessing each of the 17 feature is shown in Table 1. "Assessment & Plan" (21.18%), "Diagnosis" (16.36%), "Order" (17.17%), and "Medication" (14.53%) were the most often used features—together they constitute nearly 70% of all usage. In contrast, "Retaking

BP" (0.34%), "Procedure" (0.38%), and "Medication Side Effects" (0.22%) were rarely accessed.

B. Consecutive feature accesses

Sequential pattern analysis identified 11 maximal sequential patterns that satisfy a minimum support of 15%, shown in Table 3. ADAD (51.16%) and DADA (43.97%) are two salient patterns, indicating that clinicians often accessed "Assessment & Plan" and "Diagnosis" next to each other, and frequently switched between them back and forth. A *post hoc* analysis was conducted to determine whether "Assessment & Plan" was preceded by "Diagnosis" more often or vice versa. The result shows accessing the "Assessment & Plan" feature led in 89.18% of the ...ADAD... or ...DADA... sequence segments. Similarly, "Order" $\rightleftharpoons$ "Medication" and "Order" $\rightleftharpoons$ "Laboratory Test" are another two frequently used feature combinations. "Order" was usually accessed prior to "Medication" (72.57%) or "Laboratory Test" (71.58%). Other patterns that received significant support include "Physician Examination" $\Rightarrow$ "Assessment & Plan" $\rightleftharpoons$ "Diagnosis", which appeared in 40.17% of encounter sessions; and "Review of System" $\Rightarrow$ "Physician Examination" $\Rightarrow$ "Assessment & Plan" $\rightleftharpoons$ "Diagnosis", supported by 21.78% of patient encounters.

C. Within-session sequential patterns

Three within-session sequential patterns were identified, namely "Assessment & Plan" $\rightleftharpoons$ "Diagnosis" (0.7), "Order" $\rightleftharpoons$ "Medication" (0.65), and "Order" $\rightleftharpoons$ "Laboratory Test" (0.65). The within-session recurrence probability of each of these patterns is shown in parentheses. The "Assessment & Plan" $\rightleftharpoons$ "Diagnosis" pattern, for example, indicates that conditional on an initial use of this feature combination, there is a 0.7 chance that this feature combination will appear again later in the current clinical context. As noted earlier, "Assessment & Plan" $\rightleftharpoons$ "Diagnosis", "Order" $\rightleftharpoons$ "Medication", and "Order" $\rightleftharpoons$ "Laboratory Test" are also across-session sequential patterns discovered by SPA. Because these 'paired' features were usually accessed together, both within and across encounter sessions, they are hereby referred to as *bundled features*.

Bundled features were further collapsed to allow the detection of higher level sequential patterns. For example, AD…AD in the sequence HADAD…ADADXY was collapsed to form a new event sequence H-*K*-XY, which was then inspected by an additional pass of the sequential pattern analysis. AD…ADO ("Assessment & Plan" $\rightleftharpoons$ "Diagnosis" $\Rightarrow$ "Order") is the only new pattern emerged, supported by 15.64% of patient encounters. This pattern indicates that once a clinician completed working on the "Assessment & Plan" $\rightleftharpoons$ "Diagnosis" feature bundle, he or she may immediately move on to the "Order" section.

D. The global navigational pathway

In the Markov chain analysis, the initial probability vector π and the subsequent feature transition probabilities were estimated by computing the likelihood of switching from a given feature to other features, as recorded in the actual EHR usage. For example, suppose there were only three event sequences recorded: A**M*R***HFTXYXADAD, B**M*O*M*H***FXADABLO, and DXADAP**M*O*M*A***M. The initial probability vector π would be $\{0.33, 0.33, 0.33, 0, 0, \ldots, 0\}$, indicating that A, B or D each has a 0.33 probability of being first accessed when a clinician starts a patient encounter. The transition probability from feature M to feature R, O, H, and A would be 0.2, 0.4, 0.2, and 0.2, respectively. Zero probabilities indicate such feature transitions were not observed in the recorded EHR usage.

Table 4 shows the feature transition probability matrix A thereby achieved. Each cell designates the probability of switching from a row feature to a column feature. For example, the first row in Table 4 can be interpreted as "if a clinician is accessing the 'Assessment & Plan' feature at the moment, the probability that he or she will use 'Retaking BP' next is 0.002 ($\Pr\{S_n = \mathit{Retaking\ BP} | S_{(n-1)} = \mathit{Assessment\ \&\ Plan}\} = 0.002$); similarly, the probability that the clinician will move to 'Diagnosis' next is 0.764 ($\Pr\{S_n = \mathit{Diagnosis} | S_{(n-1)} = \mathit{Assessment\ \&\ Plan}\} = 0.764$), and so forth."

Table 5 shows the resulting Markov chain computed as πA^T. The Markov chain converges in about 7 steps, possibly because that a relatively small set of features were used consistently. The first column in Table 5 presents the initial probability vector π. The nth column presents the probability of observing each of the row features in the nth step. To better illustrate this Markov chain, we use a visualization technique to turn Table 5 into a graphical presentation, or an *EHR Feature Spectrum*, shown in Figure 4. The grayscale gradient on the spectrum is proportional to the changing probabilities of observing a row feature in each of the Markov chain states. Darker areas are associated with higher probabilities.

As shown in Table 5 and Figure 4, “Retaking BP”, “Allergies”, “History of Present Illness”, “Encounter Memo”, and “Vaccine” have the highest probabilities of appearing in Step 1. This suggests that if these features ever get used, they are most likely to be used right after a clinician starts up the EHR system. Similarly, “Medication Side Effects”, “Family History”, “Order”, “Social History”, and “Review of Systems” are most likely to be used in the second step, and so forth.

The ‘global’ navigational pathway is immediately observable from Table 5 as column maximums, which indicate which row feature is most likely to be used in a given step (the row maximums indicate the step in which a given row feature is most likely to appear). “History of Present Illness” $\Rightarrow$ “Social History” $\Rightarrow$ “Assessment & Plan” is the most likely pathway traversed by clinicians in the first three steps. After the third step, “Assessment & Plan” dominates the system’s states, because “Assessment & Plan” was the most frequently used EHR feature. Thus, many other features have high probability of transition to A. Besides this favorite global navigational pathway, several other frequent routes are also worth noting. “History of Present Illness” $\Rightarrow$ “Physical Examination” $\Rightarrow$ “Assessment & Plan” $\Rightarrow$ “Diagnosis” $\Rightarrow$ “Order” $\ldots$ and “History of Present Illness” $\Rightarrow$ “Order” $\Rightarrow$ “Physical Examination” $\Rightarrow$ “Diagnosis” $\Rightarrow$ “Assessment & Plan” $\ldots$, for example, are also frequented pathways used by clinicians to navigate in the EHR.

V. DISCUSSION

Figure 3 draws a comparison between the observed, actual navigational pattern of CRS (solid line) and the expected, ideal pathway (dotted line). The expected pathway, or the default EHR UI layout, was reached as a consensus through extensive design discussions with the system's intended users. Despite the fact that use of the EHR may cater to the specific patient care needs in each patient encounter, the usage patterns recurring overtime suggest that the actual EHR user behavior—revealed in non-intrusive observation of clinicians' routine interaction with the EHR in naturalistic settings—largely deviated from the assumed 'best' practices. This deviation may be accounted for by a few different causes: (1) unanticipated behavior in clinicians' day-to-day practice that deviates from recommended standard of delivering patient care; (2) unintended way of using the system that may lead to unintended consequences; and (3) issues associated with the system's UI and AP design, indicating new reengineering opportunities to further improve the usability of the system.

First, clinicians tended to ignore the EHR features that are intended to capture structured data entry, such as the itemized "Physical Examination" list. In contrast, free-text UI elements such as "Assessment & Plan" tended to be overutilized and accessed during a patient encounter in an unanticipated order. As the global navigational pathway indicates, after documenting in "History of Present Illness", clinicians constantly skipped all other EHR features and jumped directly to work on "Assessment & Plan". The "Assessment & Plan" feature, by its design, should be used last in an patient encounter to document summative information that highlights codified patient data entered in other respective EHR sections. This unanticipated behavior uncovered suggests that either some required patient care procedures (e.g., physical examinations) were not routinely performed, or were performed but not properly documented due to unintended use of the EHR. Such behavior could result in poor quality of documented patient data, which in the long run would impair the system's ability to generate accurate and relevant point-of-care clinical reminders and decrease the utility of recorded patient data for secondary analyses.

Second, counter to anticipation, the “Encounter Memo” feature was rarely used. “Encounter Memo” is provided as a means to document contextual information that does not fit in any other categories. End users on the design team indicated that this was a highly desired feature: it represented a means to quickly record transitory information or to pass on messages for efficient patient handoffs. The foremost position on a computer screen (top right corner) was therefore reserved for this feature because of its assumed importance. However, it was only used in 0.44% of patent encounters. With this finding in mind, the onscreen position of “Encounter Memo” may need to be changed, or additional training needs to be provided to encourage the use of this feature.

Third, some usage patterns identified suggest further improvements of the system’s UI and AP designs. “History of Present Illness”, for example, should occupy a more salient position immediately visible after a clinician enters the EHR main workspace. “History of Present Illness” is a frequently used feature and is usually accessed first when a clinician starts a patient encounter. The sequential pattern analyses also identified three *bundled features*: “Assessment & Plan” $\rightleftharpoons$ “Diagnosis”, “Order” $\rightleftharpoons$ “Medication”, and “Order” $\rightleftharpoons$ “Laboratory Test”. Clinicians often accessed these bundled features together, and frequently switch between them back and forth. Providing quick navigational aids such as hyperlink shortcuts or ‘jump-to’ buttons would greatly facilitate such frequent feature switches. Finally, the onscreen position of “Allergies” may need to be swapped with that of the “Medication Side Effects” feature. “Medication Side Effects” is less often used, and has a much higher probability of transitioning to “Allergies” instead of vice versa. Similarly, onscreen position of “Social History” and “Family History” should also be swapped. Decisions regarding the positioning of these features in the current UI proved to be inefficient.

Some of these usage patterns also suggest general design implications helpful in guiding the design of EHRs or other types of health IT applications. For example, zeros in the Markov chain transition probability matrix (Table 4) indicate that such feature transitions never occurred in practice, therefore, these features do not need to, or perhaps should not, be positioned next to each other in a software UI. When designing a stepwise guided wizard, patterns as such may help designers avoid presenting tasks in an arbitrary sequential order that may appear rather awkward to clinician users.

A. Limitations

Several limitations of this study need to be acknowledged. First, actual usage can only be learnt from a working system. Idiosyncrasies of this system would inevitably affect its end users' behavior, resulting in altered behavior being revealed. Second, the findings are derived from clinicians' use of one single EHR application. Although the general EHR features are analogous across different EHRs, their specific implementation in CRS may affect the generalizeability of the findings of this research. Third, this study was conducted in an internal medicine residency training clinic. The resident users' clinical practice can be very different from that of other types of clinicians or clinicians in other medical specialties. As such, this study is intended to *report* the actual navigational pathways traversed by the resident users, not suggesting these are necessarily preferred pathways that should be incorporated in designing other EHRs. Fourth and finally, the usage data analyzed in this study did not inclusively capture all possible EHR activities. Users reading information from a computer screen without interacting with the UI, for example, might result in neither database entries nor transitory events being recorded. There is no easy fix to this problem, however, unless more expensive (and likely more intrusive) study designs are employed such as software usability experiments using eye-tracking devices.

B. Future directions

Future efforts may consider making full use of computer-recorded transaction data generated by other types of health IT systems—to study their usage behavior in order to detect suboptimal UI and AF designs. For example, Koppel et al. (2005) and Ash et al. (2007) described several UI/AF-induced error types in clinicians' use of computerized physician order entry (CPOE) systems, such as unclear logon/logoff, failure to provide medications after surgery, inappropriate timing of alerts issuing, and juxtaposition errors (wrong selection of patients or medications made because of adjacent onscreen position of similar items) [7, 30]. The usage pattern analyses demonstrated in this paper may provide a new approach to study such issues by examining how end users navigate through a CPOE's software user interface to perform different tasks. The navigational patterns may also help suggest when and why end users develop workarounds to bypass certain system constraints, for example, skipping some of the features or using them in an inappropriate sequential order.

Future work may also consider allowing clinicians to customize their workspaces, for example to create a personalized onscreen arrangement of various EHR features. However, while it should be acknowledged that different clinicians have different practice styles, we argue a carefully designed default layout is more critical than providing a UI customization option, and subsequently relying on this option for end users to self-improve the usability of a software system. Previous research has shown that software customization is often underutilized due to numerous cognitive or practical reasons [31, 32]. To some extent, flexibility allowing for extensive customization may also facilitate practices deviating from recommended standard instead of promoting healthier behavior change. This research presents an attempt to identify a better *default* EHR UI and AF design that introduces minimum cognitive disturbance, at the same time, complies with consensus best practices in a particular healthcare setting.

VI. CONCLUSIONS

Health IT systems provide considerable promise for improving quality of care and reducing medical errors. However, these desired outcomes cannot be achieved if they are not properly used. Unfortunately, poorly designed software user interface and workflow integration often result in unusable IT systems, impeding their widespread adoption and routine use in healthcare. This paper demonstrates a novel approach for studying user behavior and usability issues of health IT applications. Actual usage of an EHR, collected from naturalistic settings with real patients, was analyzed as temporal event sequences to discover recurring usage patterns. These patterns suggest both unanticipated EHR user behavior and opportunities to further reengineer the system to improve its usability. The findings also indicate a significant gap between software designers' perception of what 'good' health IT designs are versus end users' response as unanticipated usage behavior. This mismatch may account for the poor usability of existing health IT systems, and therefore needs to be carefully addressed.

Table 1: Feature Labeling Schema and Access Frequency

Label	Feature	Frequency of use (%)
A	**A**ssessment & Plan	21.18
B	Retaking **B**P	.34
D	**D**iagnosis (past medical history)	16.36
E	Medication Side **E**ffects	.22
F	**F**amily History	1.24
G	Aller**G**ies	1.88
H	**H**istory of Present Illness (HPI)	7.26
L	**L**aboratory Test	3.58
M	**M**edication	14.53
O	**O**rder	17.17
P	**P**rocedure	.38
R	Encounte**R** Memo	.44
S	**S**ocial History	2.85
T	Office **T**est	.62
V	**V**accination	.83
X	Physical E**X**amination	6.69
Y	Review of S**Y**stems	4.43

Table 2: Constructing Event Sequences: An Example

Session Id	Event type	Time stamp
1000	H - History	10:02:11 10-22-2005
1000	A - Assessment & Plan	10:10:01 10-22-2005
1000	D - Diagnosis	10:12:01 10-22-2005
1000	D - Diagnosis	10:14:41 10-22-2005
1000	D - Diagnosis	10:17:05 10-22-2005
1000	A - Assessment & Plan	10:19:17 10-22-2005
1000	D - Diagnosis	10:24:35 10-22-2005
1000	A - Assessment & Plan	10:25:00 10-22-2005
1000	A - Assessment & Plan	10:25:23 10-22-2005
1000	D - Diagnosis	10:26:32 10-22-2005
1000	X - Physician Examination	10:26:46 10-22-2005
1000	Y - Review of Systems	10:30:11 10-22-2005

Event sequence constructed: HADDDADAADXY

Table 3: Sequential Patterns Identified

Pattern	Level of support (%)
ADAD	51.16
DADA	43.97
XADA	40.17
OMOM	32.77
MOMO	29.39
YXAD	21.78
HS	19.03
OL	18.6
OMY	16.7
LO	15.64
HO	15.01

Table 4: Feature Transition Probability Matrix

	A	B	D	E	F	G	H	L	M	O	P	R	S	T	V	X	Y
A	–	.002	.764	0	0	.002	.02	.022	.032	.083	.004	.002	.012	0	.01	.032	.016
B	.143	–	0	.048	.048	.095	.381	0	.048	.048	.048	.048	0	0	0	.048	.048
D	.152	.004	–	0	.014	.018	.097	.065	.072	.278	.025	.004	.018	.011	.051	.144	.047
E	0	0	0	–	.133	.267	.067	0	0	0	0	0	.2	0	.2	0	.133
F	0	0	.025	0	–	.1	.05	.012	.05	.1	0	0	.538	.012	0	.05	.062
G	.025	.016	0	.025	.066	–	.336	0	.098	.139	0	0	.189	0	.041	.049	.016
H	.054	.002	.006	.017	.084	.06	–	0	.122	.154	.002	.009	.193	.004	.002	.146	.146
L	.418	0	.071	0	.01	0	.041	–	.02	.276	.092	.01	0	.01	.041	.01	0
M	.128	.009	.035	0	.012	.009	.041	.017	–	.245	0	.006	.026	.003	0	.187	.283
O	.086	0	.002	0	.01	0	.014	.164	.57	–	0	0	.007	.002	.005	.045	.095
P	.632	0	.053	0	.053	0	0	0	0	.105	–	0	0	0	.158	0	0
R	.069	.069	0	.069	.069	0	.241	.034	.034	.069	0	–	0	.069	0	.034	.241
S	.032	.005	.011	0	.063	.068	.053	.005	.189	.337	0	.005	–	0	.005	.105	.121
T	.585	0	.122	0	0	0	.024	.098	0	.073	0	0	0	–	.024	.073	0
V	.51	.061	.02	0	0	0	.224	.02	.041	0	0	.041	0	0	–	.02	.061
X	.687	.005	.071	0	.002	.002	.025	.014	.007	.059	.014	0	.011	.048	.018	–	.037
Y	.145	0	.017	0	.007	0	.047	.003	.003	.037	0	0	.014	.034	0	.693	–

Table 5: The Markov Chain of Sequential Feature Accesses†

	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7
A - Assessment & Plan	.006	.071	**.165**	**.193**	**.19**	**.193**	**.191**
B - Retaking BP	.015	.008	.005	.004	.004	.004	.004
D - Diagnosis	.002	.012	.076	.149	.169	.166	.168
E - Medication Side Effects	.002	.018	.003	.002	.002	.002	.002
F - Family History	.006	.07	.026	.017	.015	.014	.014
G - Allergies	.131	.044	.029	.015	.013	.012	.012
H - History of Present Illness	**.681**	.067	.054	.048	.048	.048	.048
L - Laboratory Test	0	.008	.032	.037	.041	.043	.043
M - Medication	.021	.121	.13	.114	.109	.112	.112
O - Order	.036	.136	.133	.129	.134	.135	.135
P - Procedure	0	.002	.004	.008	.01	.011	.011
R - Encounter Memo	.036	.007	.003	.003	.003	.004	.004
S - Social History	.004	**.161**	.071	.041	.033	.031	.031
T - Office Test	0	.007	.013	.013	.012	.012	.012
V - Vaccination	.019	.008	.012	.013	.017	.018	.018
X - Physical Examination	.008	.137	.152	.131	.126	.122	.121
Y - Review of Systems	.032	.123	.093	.082	.075	.073	.074

† Column maximums are highlighted.

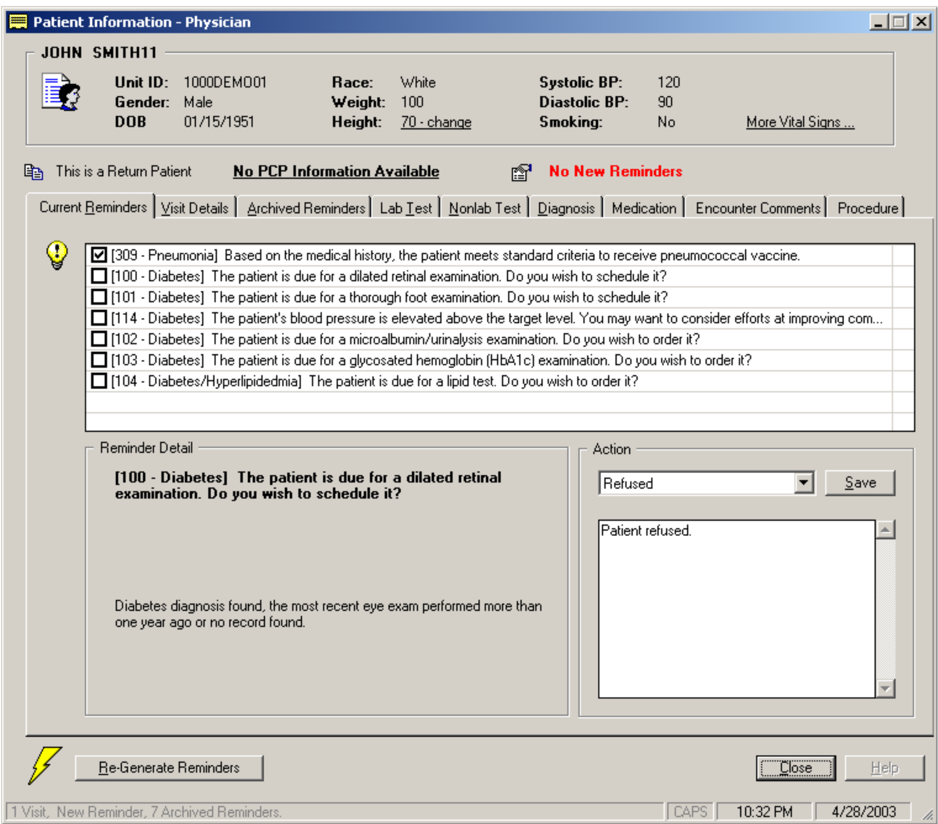

Figure 1: An Earlier User Interface

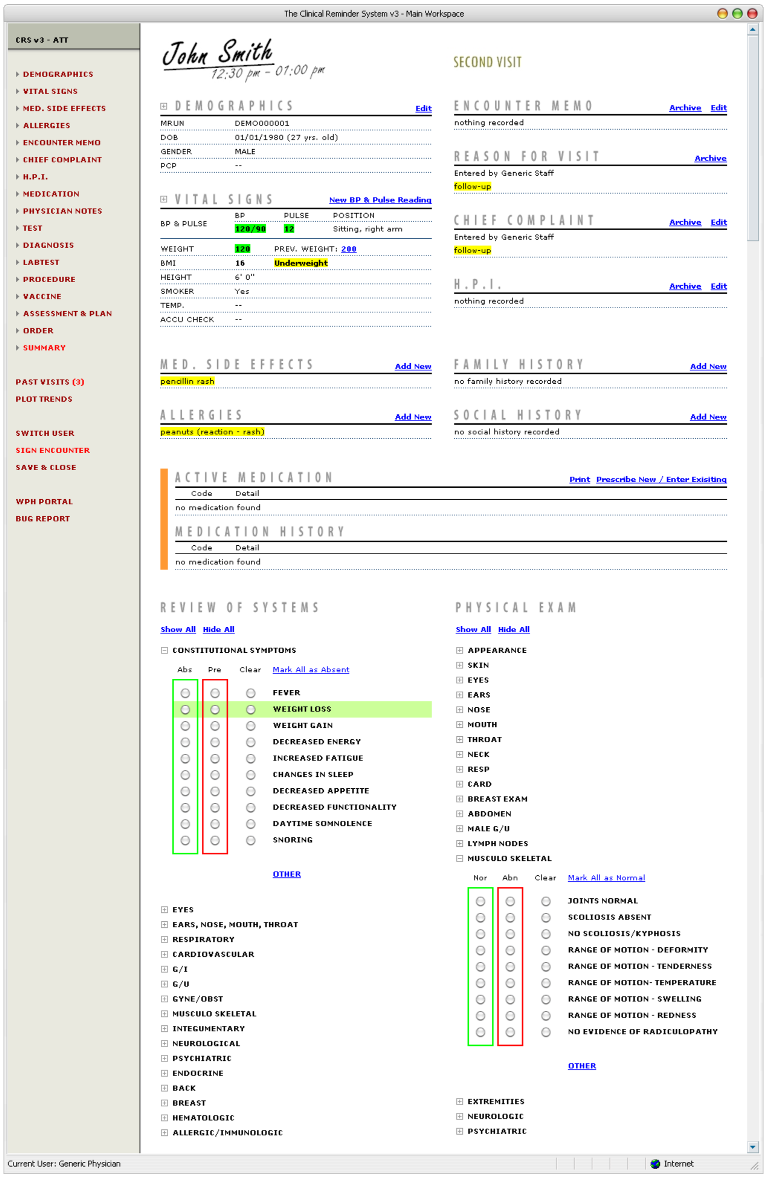

Figure 2: The Reengineered Web-Based User Interface

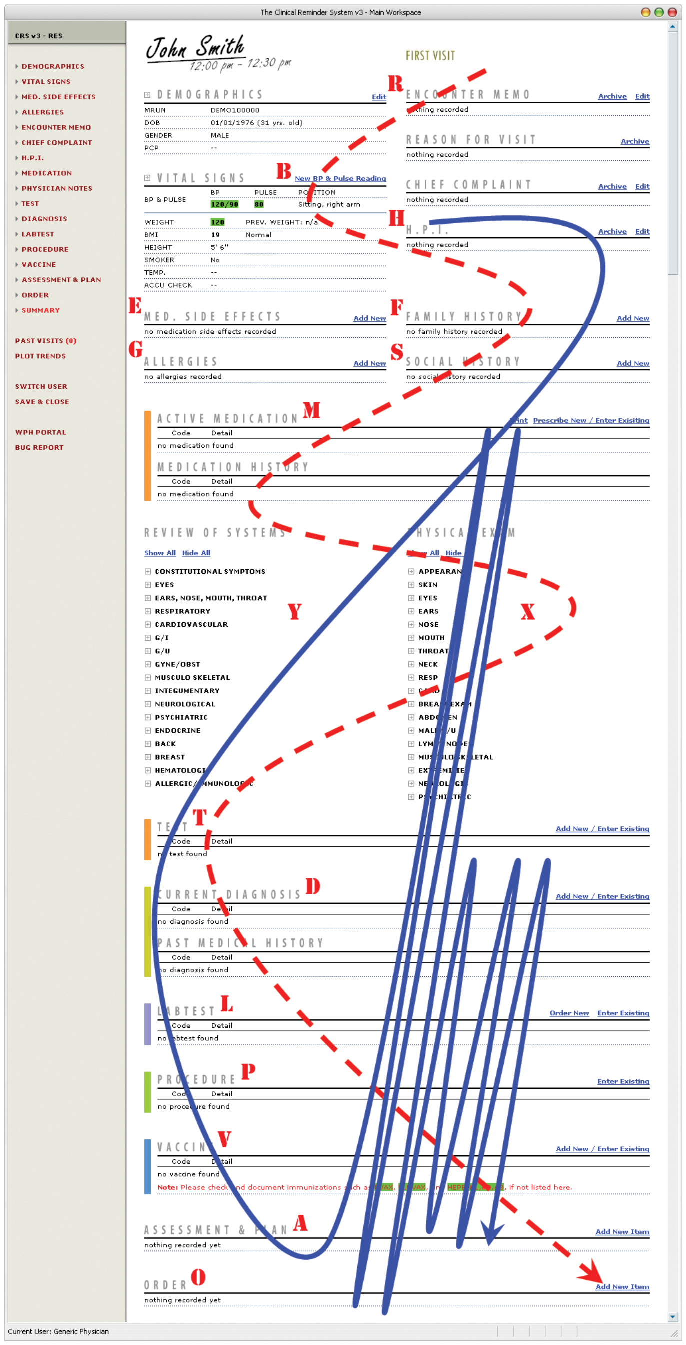

Figure 3: Onscreen Position of the EHR Features in the reengineered UI (size of the screenshot manipulated for print: approximately 1/3 of the screen will be visible at one time on a regular computer display; dotted line: anticipated navigational pathway; solid line: actual pathway observed)

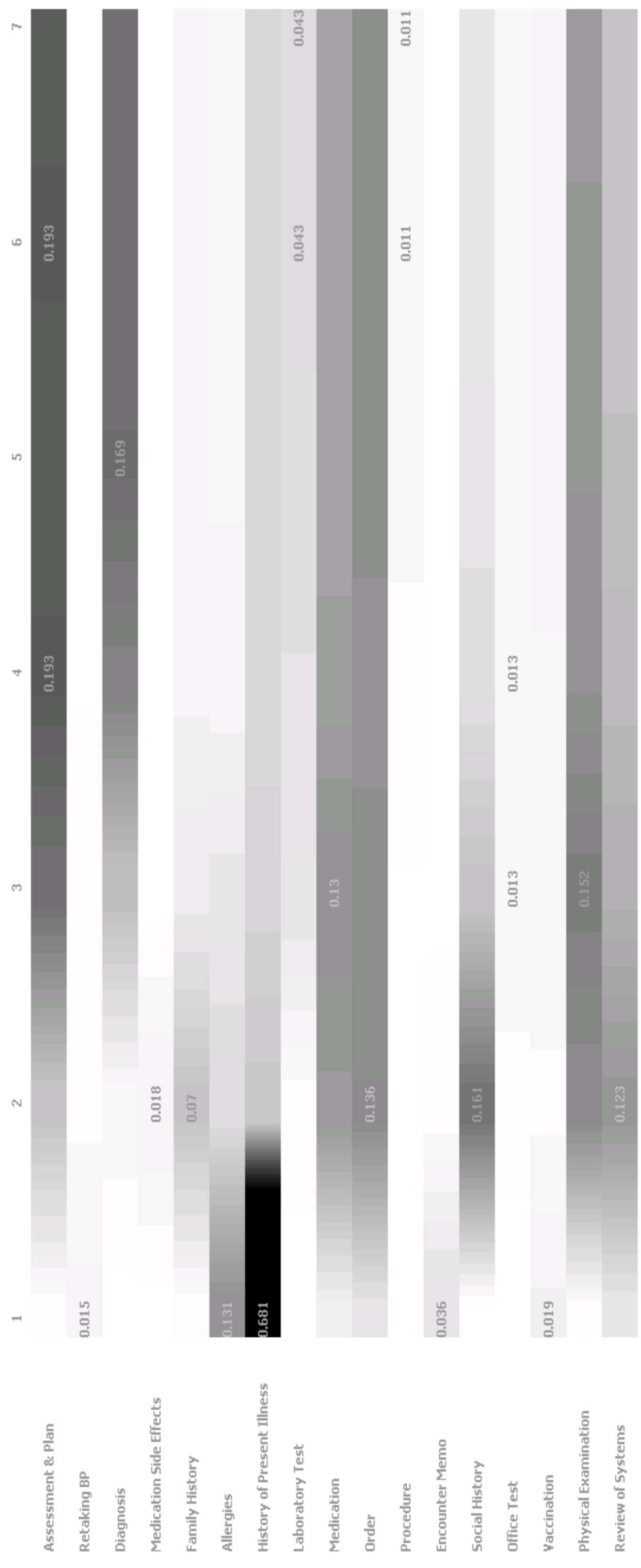

Figure 4: EHR Feature Spectrum in a Timed Space (grayscale gradient is proportional to the changing probabilities of observing a row feature at a designated time; darker areas are associated with higher probabilities; row maximums are shown)

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