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ABSTRACT

Objective was to assess the relationship between task demand, mental effort, task difficulty, and performance during physicians’ interaction with electronic health records (EHRs). Seventeen physicians performed three EHR-based scenarios with varying task demands. Mental effort was measured using eye tracking measures via task evoked pupillary responses (TEPR), blink frequency, and gaze speed; task difficulty (or user behavior) was measured using frequent mouse click patterns and task flow; user performance was quantified using two types of omission errors: (i) omission errors with no evidence of trying to complete the task and (ii) omission error with evidence of trying but unable to complete the task. The results indicated that task demand significantly increased mental effort, but not task difficulty. Task demand, mental effort, and task difficulty all predicted performance. Specifically, there was a significant relationship between (i) task demand, TEPR and omission errors with no evidence of trying to complete the task, and (ii) blink frequency, repeated search clicks and omission error with evidence of trying but unable to complete the task. In concert, results suggest that physicians’ performance during EHR interaction was negatively affected by task demands and increase in mental effort. This highlights the need for implementation of appropriate quality assurance (QA) measures, in addition to EHR usability improvement, to minimize omission errors and improve physician’s performance. Additionally, the lack of relationship between task demand and task difficulty highlights a need for further methodological and empirical studies to advance our understanding from theory to application during physician–EHR interaction.

1. Introduction

In healthcare, electronic health records (EHRs) offer the potential to improve patient care and decrease cost; however, serious unintended consequences from the implementation of these systems have emerged (Bowman, 2013). Poor usability of EHR design can “create new hazards in the already complex delivery of health care” (Lin & Stead, 2009), by increasing task demands, mental effort, and task difficulty that in turn negatively affects healthcare professionals’ performance and patient safety (Elliott, Young, Brice, Aguiar & Kolm, 2014; Peute & Jaspers, 2007; Russ et al., 2014; Vicente, 1999). For example, Hill, Sears, and Melanson (2013) found that providers seeing (on average per hour) 2.4 patients require about 4,000 mouse-clicks in EHRs during a 10-hour shift. Further, more than 1,000 adverse events associated with EHRs were reported to the Pennsylvania Patient Safety Authority in 2011 (Sparnon & Marella, 2012). Recent reports that focused on EHR-related medical malpractice identified over 80% of the reported events involve patient harm: many deaths, strokes, missed and significantly delayed cancer diagnoses, massive hemorrhage, 10-fold overdoses, ignored or lost critical lab results, etc. (Graber, Siegal, Riah, Johnston, & Kenyon, 2015).

Overall, the relationship between task demands, mental effort, task difficulty (as experienced by the user due to interaction between user and task), and performance, has been vigorously studied in many domains including human–computer interaction (Hancock & Szalma, 2003; Merat, Antilla, & Luoma, 2005; Szalma & Hancock, 2007), but not much work have been done in physician–EHR interaction arena. Specific task (e.g., information structure and information rate), individual (e.g., cognitive capabilities, knowledge, experience), and technology (e.g., usability, functionality) characteristics were related to mental effort (perceived and physiological), behavior (e.g., strategies used to perform the task), and performance (Fairclough, Venables, & Tattersall, 2005; Goodhue & Thompson, 1995; Hancock, Williams, & Manning, 1995; Merat et al., 2005; Szalma & Hancock, 2007; Zhang & Galletta, 2006). For example, in air-traffic control (ATC) setting, increased rate of information (i.e., increased number of aircrafts under control) significantly increased mental effort and degraded performance (Chen, Epps, Ruiz, & Chen, 2011;
1.1. Theoretical foundation

According to limited resource theory, increase in task demands increases mental effort necessary for task performance and thus falters or fails performance (Kahneman, 1973; Moray, 1967). Specifically, the theory suggests that the effect on performance is both due to mental effort and task difficulty (i.e., how the task is experienced) and it is dependent on the context, state, capacity, and strategy of allocation of mental resources (De Waard, 1996; Kantowitz, 1987; Parasuraman & Hancock, 2001), which seems relevant during physicians’ interaction with EHRs.

The concept of mental effort and task difficulty has been broadly studied to assess the effect of task demand on performance in other domains. This was done by associating task difficulty with operator’s adaptive strategies (or behaviors) of resource allocation that enable them to manage overall workload and regulate their performance (Merat et al., 2005; Moray, Dessouky, Kijowski, & Adapathya, 1991; Parasuraman & Hancock, 2001; Szalma, 2002). Task demand is determined by the goal that must be attained by means of task performance and it is independent of the individual (De Waard, 1996; Parasuraman & Hancock, 2001). Mental effort is defined as the amount of cognitive resources supplied to perform a task and is reflected in manifestation of physiological arousal such as pupillary dilations (Kahneman, 1973). Task difficulty is the regulated behavior or adaptable strategies used to cope with increased task demand to mitigate mental effort required to perform the task (Kantowitz, 1987; Parasuraman & Hancock, 2001).

For example, under suboptimal driving conditions, drivers adapted task difficulty by reducing driving speed as a behavior strategy to optimize their mental effort and improve performance (Da Silva, 2014; De Waard, 1996). In aviation, Boehm-Davis et al. (2007) found that under high task demands (e.g., steep descent angles and low visibility conditions) and high perceived workload, pilots managed to safely land their aircraft by using a creative strategy of speed control and glide path in order to gain time to control the landing. Similar findings were drawn from the ATC (Athènes, Averty, Puechmorel, Delahaye, & Collet, 2002; Hilburn, 2004; Histon & Hansman, 2002; Loft, Sanderson, Neal, & Mooij, 2007; Sperandio, 1971) and human–computer interaction domains (Hancock & Szalma, 2003; Hertzum & Holmegaard, 2013, Szalma & Hancock, 2007).

1.2. Study and participants

The study was conducted within the Human Factors (HF) laboratory in the department of radiation oncology at University of North Carolina, Chapel Hill, where we have created a simulated environment that closely mirrors the real clinical environment of physician–EHR interactions. The Institutional Review Board (IRB) approved the study. Seventeen resident physicians and medical students’ (6 post graduate year (PGY)-3+, 4 PGY-1, and 7 final year medical students) participated in the study. Eye movements and screen activities (computer mouse clicks) were monitored and captured using Tobii X-60 (60 Hz frequency) and Eyeworks® while participants performed one baseline and three clinical scenarios.

2. Methods

2.1. Study and participants

A brief introduction to the experiment/procedure, including eye tracking, was provided to the participants. First, to gauge participants’ physiological baseline and responses, a basic working memory task of 3-letter memorization-recall (repeated 10 times) was administered. Next, three stimulated clinical scenarios involving test patients with (urinary tract
infection [UTI], pneumonia [PN], and heart failure [HF]) were presented in the Epic© EHR playground environment (used at University of North Carolina at Chapel Hill). A 2-minute break was provided after the baseline and between the three clinical scenarios. Printed instructions describing pre-specified tasks on three routine clinical scenarios were provided next to the participant display monitor (Table 1).

### 2.3. Measures and assessment

#### Data collection

**Task demand.** The three clinical scenarios involved EHR task management for patients with UTI, PN, and HF, having variable range of tasks demands were presented in the same sequence (Mazur et al., 2016). These medical conditions were chosen because they represent some of the most common admission diagnoses to U.S. hospitals (Pfuntner, Wier, & Stocks, 2013) and therefore their management should be familiar to most practicing physicians. The UTI scenario was relatively straightforward and task demands were minimal as it required fewer decisions (4), followed by the HF (10) and PN (14) scenarios, both requiring more clinical decision making to design care for patients. Per experimental design and medical experts’ opinion, task demand was considered as nominal independent variable with 3 levels (UTI, PN, and HF); and per analysis of computer mouse clicks and perceived workload (Mazur et al., 2016) task demand was also considered as nominal independent variable with 2 levels (UTI, PN, & HF). Thus, data analysis was conducted with task demands set at 3- and 2-levels respectively.

**Mental effort.** Mental effort was quantified physiologically using pupillary data based on task evoked pupillary response (TEPR), blink frequency, and gaze velocity using recommended procedures (Beatty & Lucero-Wagoner, 2000; Poole & Ball, 2006). The pupillary data was averaged to 1 sample/sec for all the experiments. A baseline pupil size was computed based on the basic 3-letter memorization-recall experiment (repeated 10 times), and consisting of 1 second pupillary data prior to the recall of the memorized letters (averaged across 10 trials). TEPR was calculated by subtracting the baseline pupil size from clinical task pupil size. Blink frequency was calculated by dividing the total number of blinks in a given task by the task time. Gaze velocity was computed as the distance (measured in degrees) of gaze travelled between two consecutive samples (data collected at 60 samples per second) divided by the inter-sample time, as recommended by Holmqvist et al. (2011). Mental effort was considered as continuous variable in data analysis.

**Task difficulty.** Task difficulty was quantified based on participant’s behavior (strategic approach) to perform the task, i.e., by identifying and counting repeated patterns of mouse clicks and task flow analysis. Two researchers independently watched the recorded videos of each scenario captured using Eyeworks© software and coded mouse clicks into following three categories: (1) navigation clicks (e.g., moving from one tab to another for navigational purposes); (2) decision clicks (e.g., selecting a test or medication to order or cancelling a selected order or search result); and (3) Input clicks (e.g., placing the mouse cursor into the search box to type search terms). Any discrepancies (e.g., in some instances, navigation, and decision click codes were swapped) were resolved during our weekly meetings. Commonly occurring click patterns were extracted from the sequences using two-pass approach adapted from Guo, Gomez, Ziemkiewicz, and Laidlaw (2016). The first pass finds the most frequently occurred and possibly overlapping patterns, while the second pass segments each sequence into a series of patterns found in the first pass or.

### Table 1. Description of three clinical scenarios and list of instructed tasks for each scenario.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Instructed tasks to be performed</th>
</tr>
</thead>
</table>
| (1) Urinary tract infection (UTI) | (1) Review the clinical and physical exam notes  
|                    | (2) Specify low risk for venous thromboembolism (VTE) prophylaxis  
|                    | (3) Order any necessary urine test(s)  
|                    | (4) Check results of tests(s)  
|                    | (5) Order the appropriate treatment for the patient                                                                 |
| (2) Pneumonia (PN) | (1) Review the clinical and physical exam notes  
|                    | (2) Specify low risk for venous thromboembolism (VTE) prophylaxis  
|                    | (3) Write admission orders:  
|                    | - Admit to Med wing “G”  
|                    | - Supplemental O₂/nasal cannula, wean per nursing  
|                    | - IV antibiotics; arterial blood gas (ABG); blood and sputum cultures; Posterior-anterior and Lateral chest X-ray (PA/Lat CXR)  
|                    | - AM Labs; Complete blood count with differential, basic metabolic pane (BMP)  
|                    | (5) Check results of tests and PA Lat CXR  
|                    | (6) Order Computed Tomography (CT) of chest w/o contrast  
|                    | (7) Check results of CT  
|                    | (8) Change to oral antibiotics and write discharge order; schedule for follow-up to Medicine clinic in 1 week                                                                 |
| (3) Heart failure (HF) | (1) Review the History and Physical. This contains pertinent clinical history as well as physical exam  
|                    | (2) Specify high risk for venous thromboembolism (VTE) prophylaxis  
|                    | (3) Sub cutaneous heparin  
|                    | (4) Order labs: complete blood count (CBC), Chemistry, trans thoracic echocardiogram (TTE)  
|                    | (5) Check results of labs  
|                    | (6) Write admission orders including daily weights and low salt diet  
|                    | (7) Restart meds  
|                    | (8) Tobacco cessation consult  
|                    | (9) Order intravenous (IV) Lasix  

Note: Ambulatory, out-of-bed and Education are sufficient prophylaxis.
singleton actions. The algorithm merges patterns with clicks appearing in the same order but for different number of time windows during the task. For example, a stream of three decision clicks is considered the same as a stream of four decision clicks, and their occurrences are combined when ranking patterns by frequency during the first pass. Patterns that are mutually exclusive (i.e., end of one pattern not the same as the beginning of another pattern) were considered for analysis. The patterns included in the study were (1) editing order details that involved a decision click (to select the order), multiple input clicks (to provide details like, dose, start date, frequency, comments, reason for order, etc.), and a decision click to accept the edits (represented as DI ***D***); (2) making orders that involved multiple navigation clicks while reviewing notes or admission orders and then navigating to place (or select) multiple orders (represented as N ***D***); (3) review/exploitation of orders that involved navigating to orders to review placed/selected orders or explore hidden sub-orders by expanding the listed orders (represented as NDN ***m***); (4) searching for orders that involved navigating to the search page, then searching for an order using keyword(s), followed by multiple selection (or cancellation of returned search results followed by a new keyword search) of the orders (represented as (NID ***m***).

Task difficulty was also quantified using task flow, measured as the number of deviation from the instructed task sequence as presented in Table 1. For example (e.g., UTI scenario), if participant revisited (repeated) task 2 after performing (or during performance of) task 3, the deviation was counted as ‘1’. The task flow was quantified by counting total number of repeated tasks obtained via video analysis. Task difficulty was considered as nominal variable in data analysis.

**Performance.** Performance was quantified using two types of omission errors, (1) omission error with no evidence of trying to complete the task, and (ii) omission error with evidence of trying but unable to complete the task (e.g., tried but failed to complete the task like could not find medication or test; incorrectly/partially performed the tasks like ordering incorrect/insufficient medication or test). Two researchers evaluated performance and categorization of errors via video analysis. This was further reviewed and confirmed by an expert physician using the registry of completed orders and video recordings. If participant made both types of omission errors in a given scenario, their performance was coded as ‘error’ accordingly in each of the categories for relationship testing. Performance was considered as nominal dichotomous variable (no error versus omission error with no evidence of trying to complete the task; and no error versus omission error with evidence of trying but unable to complete the task) in data analysis.

**Data analysis.** Before data analysis, we completed tests for normality and equal variance for all study variables using Shapiro–Wilks’s and Bartlett test respectively. Results indicated that assumptions were satisfied (normality: all $p > 0.05$; equal variance: all $p > 0.05$).

A series of univariate least square (or nominal logistic) regression analyses were performed to assess the relationship between task demand (3- and 2-levels), mental effort, and task difficulty, as represented in Figure 1. Task demand was considered as independent variable, whereas mental effort and task difficulty were considered as dependent measures. Participants were included in the analysis and considered as random factor. A post-hoc analysis using Tukey’s HSD was performed to assess the significance between the three levels of task demand. Next, all variables (task demand, mental effort, and task difficulty) were included in a multivariable binomial logistic regression analysis to assess the relationship with performance. An alpha level of 0.05 was set for significance testing. All analyses were performed using JMP® 13 software and SPSS version 23®.

### 3. Results

Descriptive statistics of mental effort, task difficulty, and performance for three clinical scenarios (UTI, PN, HF) are provided in Table 2.

#### 3.1. Task demand

**Relationship with mental effort**

There was a significant negative effect of task demands on blink frequency (3-levels: $F(2,29) = 7.4, p = 0.003$; 2-levels: $F(1,29) = 15, p < 0.001$), indicating that blink frequency was

<table>
<thead>
<tr>
<th>Measures</th>
<th>UTI</th>
<th>PN</th>
<th>HF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mental effort</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TEP in mm$^3$ [mean(sd)]</td>
<td>0.15 (0.14)</td>
<td>0.16 (0.17)</td>
<td>0.14 (0.16)</td>
</tr>
<tr>
<td>Blink Freq. as #/min$^1$ [mean(sd)]</td>
<td>8.7 (3)</td>
<td>4.3 (2)</td>
<td>4.2 (3)</td>
</tr>
<tr>
<td>Gaze Speed in degrees/sec$^1$ [mean(sd)]</td>
<td>138 (46)</td>
<td>134 (29)</td>
<td>139 (43)</td>
</tr>
<tr>
<td><strong>Task difficulty</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Editing order details</td>
<td>2</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>(Pattern: DI <em><strong>D</strong></em> [count])</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Making orders</td>
<td>32</td>
<td>64</td>
<td>36</td>
</tr>
<tr>
<td>(Pattern: N <em><strong>D</strong></em> [count])</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reviewing/exploration of orders</td>
<td>14</td>
<td>20</td>
<td>14</td>
</tr>
<tr>
<td>(Pattern: NDN <em><strong>m</strong></em> [count])</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Searching for orders</td>
<td>8</td>
<td>19</td>
<td>12</td>
</tr>
<tr>
<td>(Pattern: NID <em><strong>m</strong></em> [count])</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task flow [count]</td>
<td>8</td>
<td>13</td>
<td>10</td>
</tr>
<tr>
<td><strong>Performance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Omission error with no evidence of trying to complete the task [count]</td>
<td>1</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>Omission error with evidence of trying but unable to complete the task [count]</td>
<td>2</td>
<td>8</td>
<td>7</td>
</tr>
</tbody>
</table>

$^1$The eye data on one participant was discarded due to excessive loss of data (>40%) for the three clinical scenarios.

$N$: navigation clicks; $D$: Decision clicks; $I$: Input clicks; $N^m$: two or more consecutive navigation clicks; $D^m$: two or more consecutive decision clicks; $I^m$: two or more consecutive input clicks.
significantly lower in PN and HF compared to UTI scenario \((p < 0.05)\).

**Relationship with task difficulty**

There was no significant effect of task demand (both 3- and 2-levels) on task difficulty \((p > 0.05)\).

### 3.2. Performance

**Relationship with task demands, effort, and task difficulty**

There was a significant positive relationship between omission errors with no evidence of trying to complete the task and task demand, and mental effort measured by TEPR (with 3-level task demand: \(\chi^2(9,n=51) = 25, p = 0.003\); with 2-level task demand: \(\chi^2(8,n=51) = 14, p = 0.05\)). The odds of making an error in PN case was 15 and 10 times more likely compared to HF and UTI cases respectively for 3-levels of task demand; whereas the odds of making an error in PH & HF case grouped together was 16 times more likely compared to UTI case for 2-levels of task demand. Also, TEPR was 110% more dilated in participants who made an error compared to participants with no error \((p = 0.002)\) (Table 3).

There was a significant negative relationship between omission errors with evidence of trying but unable to complete the task and mental effort measured by blink frequency and a significant positive relationship with click pattern, specifically to healthcare domain. First, we found that EHR-related task demands significantly increases mental effort, which is in line with previous findings including aviation (Ayaz et al., 2010; Colle & Reid, 2005; De Riceout, Kuperus, Post, & Mulder, 2008; Hancock et al., 1995; Hoffman, Pene, Rognin, & Zeghal, 2003; Lee, Kerns, Bone, & Nickelson, 2001), nuclear power (Byun & Choi, 2002; Liang et al., 2009), human–computer interaction (Cullen, Dan, Rogers, & Fisk, 2014; Hertzum, & Holmegaard, 2013), and in healthcare (Carswell, Clarke, & Seales, 2005; Mazur et al., 2016; Young, Zavelina, & Hooper, 2008; Yurko, Scerbo, Prabhu, Acker, & Stefanidis, 2010; Zhang, Padman, & Levin, 2012). Specifically, we found blink frequency to be a predictor of mental effort as evoked by task demands. Similar findings have been reported by other studies in various domains, commonly indicating that a lower blink frequency is assumed to indicate a higher visual workload (Brookings, Wilson, & Swain, 1996; Bruneau, Sasse, & McCarthy, 2002; May, Kennedy, Williams, Dunlap, & Brannan, 1990; Mosaly, Mazur, & Marks, 2016; Poole & Ball, 2006; Zheng et al., 2012).

Second, we found that both task demands and mental effort as measured by TEPR to be predictors of performance, specifically omission errors with no evidence of trying to complete the task (Table 3). We found that participants made more omission errors in PN case, followed by HF case when compared to UTI case, and had their TEPR dilated 110% more than participants that had no errors. These findings are in line with previous findings indicating that higher task demands lead to increase in mental effort that increases errors in various domains (Da Silva, 2014; Stetina, Groves, & Pafford, 2005) including physician–EHR interactions (Ariza, Kalra, & Potts, 2015; Mazur et al., 2016; Mosaly et al., 2016; Zhang & Walji, 2011).

Third, we found the increase in mental effort and task difficulty (click pattern) to be predictors of performance, specifically omission errors with evidence of trying but unable to complete the task (Table 3). We found that participants who made errors had significantly lower blink frequency (decreased by 50%) and exhibited frequent searching for orders (NID\(^{10}\)) clock pattern behavior.

To further understand the task difficulty based on click behavior, we assessed the videos and found that participants utilized two different procedures, i.e., templated versus non-templated, while making orders within computerized physician order entry (CPOE). Templated procedure enabled

### 4. Discussion

There are number of key contributions of our study to the body of knowledge of human–computer interaction, especially to healthcare domain. First, we found that EHR-related task demands significantly increases mental effort, which is in line with previous findings including aviation (Ayaz et al., 2010; Colle & Reid, 2005; De Riceout, Kuperus, Post, & Mulder, 2008; Hancock et al., 1995; Hoffman, Pene, Rognin, & Zeghal, 2003; Lee, Kerns, Bone, & Nickelson, 2001), nuclear power (Byun & Choi, 2002; Liang et al., 2009), human–computer interaction (Cullen, Dan, Rogers, & Fisk, 2014; Hertzum, & Holmegaard, 2013), and in healthcare (Carswell, Clarke, & Seales, 2005; Mazur et al., 2016; Young, Zavelina, & Hooper, 2008; Yurko, Scerbo, Prabhu, Acker, & Stefanidis, 2010; Zhang, Padman, & Levin, 2012). Specifically, we found blink frequency to be a predictor of mental effort as evoked by task demands. Similar findings have been reported by other studies in various domains, commonly indicating that a lower blink frequency is assumed to indicate a higher visual workload (Brookings, Wilson, & Swain, 1996; Bruneau, Sasse, & McCarthy, 2002; May, Kennedy, Williams, Dunlap, & Brannan, 1990; Mosaly, Mazur, & Marks, 2016; Poole & Ball, 2006; Zheng et al., 2012).

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To further understand the task difficulty based on click behavior, we assessed the videos and found that participants utilized two different procedures, i.e., templated versus non-templated, while making orders within computerized physician order entry (CPOE). Templated procedure enabled
Table 4. Describes the % (n) of participants who followed templated vs. non-templated procedure and made (or not made) omission errors.

<table>
<thead>
<tr>
<th>Errors</th>
<th>No Errors</th>
<th>Omission Errors with no evidence of trying</th>
<th>Omission Errors with evidence of trying</th>
</tr>
</thead>
<tbody>
<tr>
<td>Followed Templated Procedure</td>
<td>50% (16/32)</td>
<td>28% (9/32)</td>
<td>22% (7/32)</td>
</tr>
<tr>
<td>(63% [n=32])</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Followed Non-templated Procedure</td>
<td>36% (7/19)</td>
<td>11% (2/19)</td>
<td>53% (10/19)</td>
</tr>
<tr>
<td>(37% [n=19])</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

participants to access custom “Order Sets” via “Admissions” module (listing only the orders relevant to the selected reason [diagnosis] for admission). On the other hand, non-templated procedure enabled participants to access “Order Sets” directly, which required “free text search”, for orders to be placed (thus, frequent search pattern). We found that participants who followed templated procedure had more omission errors with no evidence of trying to complete the task than participants who followed non-templated procedure; whereas participants who followed non-templated procedure had more omission errors with evidence of trying but unable to complete the task, than participants who followed templated procedure (Table 4).

Interestingly, these findings could be related back to the concepts of limited resource theory (Broadbent, 1958; Kahneman, 1973; Meister, 1976; Sperandio, 1971). That is, we believe that participants who used templated procedure experienced more mental effort (i.e., increased TEPR) that potentially contributed to omission errors as they “stopped” paying attention to our instructed list of tasks (attention tunneling or narrowing), and instead focused their attention on the listed orders presented in the Epic EHR system after they admitted the patient using “Admissions” module. For example, in PN case, 3 of the 17 participants using templated procedure checked “high risk for venous thromboembolism (VTE) prophylaxis” (high risk of blood clots) instead of “low risk for venous thromboembolism (VTE) prophylaxis” as instructed. These orders were presented in the EHR as a list format as “VTE Risk Category – High” being listed first followed by “Low Risk of VTE”, with a check box in front of them. Participants chose the first box on the list by seeing the term VTE and not reading the complete phrase (term “High” was presented at the end of the phrase and term “Low” was presented at the beginning of the phrase for VTE risk), thus leading to an unconscious human error. Similar issues were also seen for orders like “sputum culture” (to find bacteria or fungi that are cause infection of the lungs or the airways leading to the lungs) for PN. Such challenges might be especially relevant during handoffs and cross-cover situations (Mazur et al., 2016; Mosaly et al., 2013). Our findings emphasize that some task-related characteristics that must be exercised by physicians when using templates in EHRs (e.g., decision rate per EHR display space, complexity of decisions, relationship between decisions) could enhance or constrain creative clinical thinking and promote automation (Hartzband & Groopman, 2008). In addition to task characteristics, our findings also highlight some technological characteristics (e.g., usability, functionality, search engines) to minimize mental effort as well as implementation of proper quality assurance (QA) check to assure self-regulation (or slow-down) of physicians’ behavior to facilitate careful check of their work before approval.

On the other hand, participants who followed non-templated procedure were unable to complete instructed tasks despite the use of variety of keywords and multiple searches, which resulted in lower blink frequency due to increased mental effort via visual load. It is possible that these participants lacked proper training on keyword searches to effectively interact with EHR’s database and/or sub-optimal functionality of EHR’s search databases itself. For example, when using search keywords like “VTE”, “high VTE, or “high risk venous”, database would return only “low risk for VTE prophylaxis”, resulting in a conscience human error (e.g., giving up search effort and selecting low instead of high VTE; which, itself seemed to some degree as a surprising behavior that compels further investigation). Similar behaviors were also seen for orders like “subcutaneous heparin” (used as anticoagulant injection to minimize blood clots), “Trans thoracic echocardiogram (TTE)” (a type of echocardiogram), and “IV Lasix” (to treat acute pulmonary edema), all exhibiting frequent multiple loops of repeated search behavior. Such challenges are often evident in real clinical settings where physicians, when unable to finds orders in EHRs, would delegate the task to their subordinates (i.e., to nurses or resident physicians) to complete the task. Zhang, Padman, and Levin (2014) also found similar issues with Epic EHR system while using templated versus non-templated procedures for order sets. They discussed advantages and disadvantages of one procedure over the other and recognize that usability improvement for the design of the order sets may not be the best solution in all applications. Our findings highlight the opportunity to use click patterns as a QA metric (e.g., flagging some interactions [great number of search patterns] as suboptimal with likelihood of error) in addition to usability improvement may improve performance. Similar efforts were done by Zheng, Padman, Johnson, and Diamond (2009) where they found that some of the navigational patterns in EHRs significantly deviated from the ideal patterns and therefore understanding these task difficulties or undesirable user behaviors characteristics may help in informing corrective actions such as focused user training or continued system reengineering.

Other highly reliable industries monitor and model human behaviors and interaction with computers to ensure safety (Loft et al., 2007; Parasuraman & Hancock, 2001; Sperandio, 1971). Thus, tracking users’ behavior during EHR interaction could be useful to improve human performance (e.g., via constructive feedback) (Mazur et al., 2017), offer suggestions regarding suboptimal usability and functionality (Zhang et al., 2014) of EHRs and increase patient safety (Edwards, Moloney,
Jacko, & Sainfort, 2008; Middleton et al., 2013). Overall, we found that most of our investigated relationships to be in line with previously established relationship within the HCI domain. However, the lack of relationship between task demands and task difficulty suggests that further methodological and empirical studies are needed to advance our knowledge on ways to quantify task difficulty during physicians’ interactions with EHRs. Future research could also explore the ways to examine the relationship between mental effort and task difficulty, while considering potential tradeoffs between interaction speed and accuracy.

There are some limitations to this study, and thus caution should be exercised in generalizing our findings. First, study findings are based on 17 participants (resident physicians and medical students) and three clinical scenarios that are considered to be the most commonly performed tasks in the hospital environment (Pfuntner et al., 2013). However, all participants in the study were knowledgeable in performing these common tasks. Second, techniques employed to calculate TEPR, blink frequency and gaze velocity are challenging and are not perfect. For example, pupillary dilation is affected by change in illumination of the display, gaze etc. Any loss of the pupillary measures is coded as ‘0’ in the raw data and hence the software has over or under estimated eye blinks, and change in participants’ position (leaning toward and away from the display monitor), and repeatedly looking at the keyboard to perform typing may have affected the eye gaze, pupil and blink data. Therefore, we performed visual inspection of raw pupillary data to identify potential outliers and data that was considered invalid was discarded (and linearly interpolated for pupillary data), based on the recommendation provided by Beatty and Lucero-Wagoner (2000), Holmqvist et al. (2011) and Marshall (2005). Third, quantifications of task difficulty and performance are challenging and could be inexact. Therefore, two researchers independently reviewed the videos and coded mouse clicks (with discrepancies resolved during weekly meetings) before computerized sequences algorithms were used (Guo et al., 2016). We also had an experienced physician verifying our performance coding.

4.1. Conclusion

We found that physicians’ performance during EHR interaction was negatively affected by task demands and increase in mental effort. The results also suggest that tracking task difficulty based on users’ behavior (e.g., click patterns) could be used as a QA metric to predict performance. Overall, our findings are aligned with prior research indicating that high task demands evoke high mental effort and affect performance. However, the lack of relationship between task demand and task difficulty highlights a need for further methodological and empirical studies to advance our understanding of physicians’ interactions with EHRs. In concert, our findings might bring the necessary knowledge, and urgency to help designers improve usability of EHRs, and healthcare organizations to choose appropriate EHRs and develop training methods to improve quality and patient safety.

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