Time-motion examination of electronic health record utilization and clinician workflows indicate frequent task switching and documentation burden

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Abstract

Clinical documentation burden has been broadly acknowledged, yet few interprofessional measures of burden exist. Using interprofessional time-motion study (TMS) data, we evaluated clinical workflows with a focus on electronic health record (EHR) utilization and fragmentation among 47 clinicians: 34 advanced practice providers (APPs) and 13 registered nurses (RNs) from: an acute care unit (n=15 observations [obs]), intensive care unit (n_{obs}=14), ambulatory clinic (n_{obs}=3), and emergency department (n_{obs}=15). We examined workflow fragmentation, task-switch type, and task involvement. In our study, clinicians on average exhibited 1.4±0.6 switches per minute in their workflow. Eighty-four (19.6%) of the 429 task-switch types presented in the data accounted for 80.1% of all switches. Among those, data viewing- and data entry-related tasks were involved in 48.2% of all switches, indicating documentation burden may play a critical role in workflow disruptions. Therefore, interruption rate evaluated through task switches may serve as a proxy for measuring burden.

Introduction

Over one third of nurses and nearly half of all physicians experience some degree of burnout due to chronic work-related stress.[1,2] Driven by individual and institutional factors such as excessive workloads, process inefficiencies (e.g., frequent interruptions),[3,4] technological advances, and changes in care delivery (among other factors),[5] professional burnout is characterized by three main symptoms: inefficiency, emotional exhaustion, and depersonalization.[6] The growing body of literature has demonstrated a compelling association between burnout and the unintended negative consequences, including increased medical errors, poorer patient outcomes, decreased adherence to practice guidelines, and risks to patient safety and care quality.[7-10]

The Quadruple Aim emerged to address the growing epidemic of burnout and dissatisfaction among healthcare professionals.[11] For example, the significant role of electronic health records (EHRs) and other health information technology tools on the “deterioration of work conditions and quality, and increased dissatisfaction of health care providers” are well-documented.[12] An extension to the Institute for Healthcare Improvement’s Triple Aim framework for optimizing the performance of health systems for patients, which include: 1) enhancing care experience, 2) improving population health, and 3) reducing healthcare costs,[13] the Quadruple Aim focuses on improving the well-being of providers.[2] This fourth aim functions as a foundational element for all other aims to be realized in healthcare as it is correlated with patient safety and care quality.[14] Due to this new framework, some have proposed that measures of workforce engagement and burnout should be developed to quantify the experience of providers,[2] and therefore, inform institutional strategies like targeted interventions to improve EHR usability, interoperability, and administrative burden.[15,16] The implementation of EHRs has been of particular interest for alleviating burnout. Studies on the maturation of EHR systems indicate that clinician stress do not return to baseline levels even months after implementation.[17,18] Broad adoption of EHRs in the last decade has been attributed to increased documentation burden, as well as frequent interruptions and information overload among clinicians.[5,10,19] And yet, limited measures to quantify the extent of EHR burden exist.[5]

Examination of clinical workflows is essential for understanding the unintended consequences of EHR design and usability on efficiency, documentation, cognitive overload, and safety. Considered the gold standard method for quantifying clinical workflows,[20,21] time-motion studies (TMSs) have been extensively used to assess healthcare delivery costs, evaluate the effects of health information systems implementation, and characterize allocation of time across clinicians’ tasks. Prior TMSs examining clinical workflows have largely involved homogenous populations of clinicians, restricting their capacity to comparatively evaluate burden across roles and practice settings.[21-24]

Concurrently, previous analyses conducted on TMS data have relied on average aggregated times spent on tasks to quantify workflow, which lack standardization and yield inconsistent results.[21,25] In this study, we examine the results of a TMS performed among clinicians of distinct roles and practice settings using an interprofessional taxonomy developed and validated by our team. These data were collected as part of the pre-implementation phase of a commercial EHR system evaluation study on clinician workflow and documentation burden which will be used to compare against post-implementation data.

Methods

From January 2019 to January 2020, we collected observational time-motion data at a large academic northeastern medical center in the United States as a part of a broader evaluation study on the implementation of a new commercial EHR system.[20] These pre-implementation data were collected in an acute care unit (ACU), intensive care unit (ICU), ambulatory clinic, and emergency department (ED), which operated under Allscripts Sunrise EHR system at the time of our study.[23] A locally-developed, interoperable EHR data-viewing system for archived data called iNYP was also available. In these settings, trained observers—using our interprofessional taxonomy[20]—conducted time-motion observations of clinicians grouped by two functional roles: 1) registered nurses (RNs), and 2) advanced practice providers (APPs). APPs were comprised of attending physicians, resident physicians, physician assistants, and nurse practitioners. Previously, our research group has published on the development and validation of the interprofessional taxonomy used in this study, which included interobserver reliability sessions.[20] In these interobserver reliability sessions, two observers concurrently conducted observations for 1.5 to 2 hours while following and the same clinician. Interobserver reliability data were analyzed for each observer to establish reliability prior to study data collection.[20,27]

The taxonomy is comprised of three broad functional categories: 1) tasks performed by the clinician (n=25), including clinical information systems (CIS)-related tasks, defined as any activity requiring computerized systems, 2) physical location where tasks occurred (n=6), and 3) communication in which the clinician engaged (n=7). CIS-related tasks consisted of the following (n=12): *entering data*, *viewing data* (including archived patient data), *documenting handoff/sign-out*, *log into EHR*, *log out of EHR*, *medication administration*, *medication reconciliation*, *smartphone clinical messaging app*, *entering orders*, *viewing patient list/schedule*, *transcribing*, and *use of other CIS*, such as telemetry monitor (Table 2). Data were electronically captured via tablets using the Time Capture Tool (TimeCaT), a web application that supports the collection of time-motion task, location, and communication data.[27] TimeCaT facilitates the capture of one active task per category at any time during the observation such that a clinician's location, activity, and conversations could be recorded concurrently—a proxy measure for multitasking.[20] Clinicians were invited to participate in observations based on availability and willingness to participate (i.e., convenience sampling). All ACU, ICU, and ambulatory clinic observations were performed during day-shift hours throughout the weekday, while ED observations included night-shifts and weekends (Figures 1 & 2). Fifty observations were conducted for no more than 4 hours at a time. We restricted our analysis to observations to which data were complete. Lastly, to ensure better workflow continuity, we also restricted our analyses to observations ≥2 hours in length.

Table 1. Characteristics of clinicians observed in the TMS

	Advanced Practice Provider n (%)	**Registered Nurse n (%)**	**Total n (%)**
Total*	34 (72.3)	13 (27.7)	47 (100.0)
Location			
Acute care	7 (20.6)	8 (61.5)	15 (31.9)
Intensive care	9 (26.5)	5 (38.5)	14 (29.8)
Ambulatory	3 (8.8)	--	3 (6.4)
Emergency	15 (44.1)	--	15 (31.9)
Age			
18-24	1 (2.9)	1 (7.7)	2 (4.3)
25-34	26 (76.5)	5 (38.5)	31 (66.0)
35-44	3 (8.8)	4 (30.8)	7 (14.9)
45-54	1 (2.9)	--	1 (2.1)
55-64	--	1 (7.7)	1 (2.1)
Unknown/refused to answer	3 (8.8)	2 (15.4)	5 (10.6)
Gender			
Male	10 (29.4)	1 (7.7)	11 (23.4)
Female	21 (61.8)	12 (92.3)	33 (70.2)
Unknown/refused to answer	3 (8.8)	--	3 (6.4)

*Based on row percentages

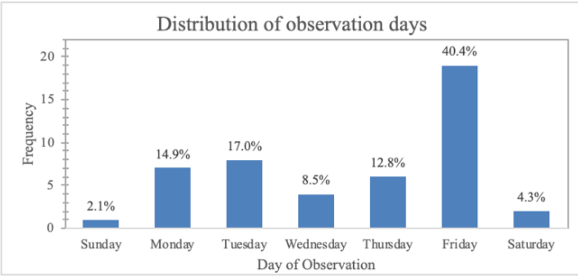


Figure 1. Distribution of observation days

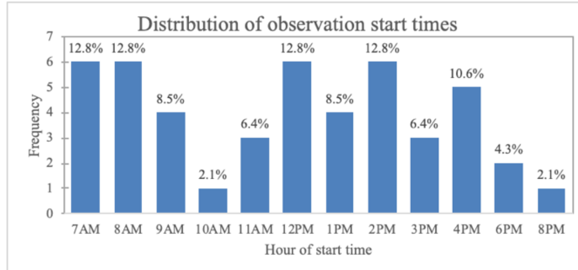


Figure 2. Distribution of observation hours

Table 2. Concept definitions and associated proposed measures of burden

Concept	Definition	Measurement reported
CIS-related tasks	(1) Entering Data* (2) Entering Orders* (3) Documenting Handoff/Sign-out* (4) Viewing Data** (5) Viewing Patient List/Schedule** (6) Log into EHR (7) Log out of EHR (8) Medication Administration (9) Medication Reconciliation (10) Smartphone Clinical Messaging App (11) Transcribing (12) Use of Other Clinical Information System	See task involvement
Workflow fragmentation	Frequency of task switches per observation over total time observed (i.e., *task-switch rate*)	Mean switches per minute per observation
Magnitude of fragmentation	Average time spent on a single task or task category prior to switching tasks (i.e., *average duration*)	Mean duration in seconds per task type
Task-switch type	Categories of task sequence pairs that are comprised of two temporally consecutive tasks for all task segments in each observation	Proportion of switch type over all switch types present in data
Task involvement [in task switches]	Frequency at which a specific task appears in sequential task sequence pairs, independent of whether it is in the initiating or the succeeding task position	Proportion of task volume over volume of all task-switch types present in data
Impact of task-switch types	Using the Pareto distribution, subset of task-switch types among all task-switch types presented (i.e., proportion) that account for the top 80.0% of the rank-frequency distribution of task switches	Task-switch volume-to-type ratio

*Tasks associated with data entry
**Tasks associated with data viewing

Descriptive and sequence analyses were conducted to examine: 1) workflow fragmentation (i.e., frequency and magnitude of task switching), 2) task-switch type, and 3) task involvement in task switches, stratified across clinician role (i.e., APP vs. RN) and practice setting (i.e., ACU, ICU, ambulatory clinic, and ED). We similarly operationalized our measures of *workflow fragmentation* and *magnitude of workflow fragmentation* according to workflow quantifiers proposed in Zheng et al.[25] In this paper, we define *workflow fragmentation* as the frequency of task switches that occur *per minute* for each observation; we conveniently refer to this measure as *task-switch rate*. A workflow represents a consecutive sequence of temporally-related tasks that unfolded dynamically. Therefore, we characterized *magnitude of workflow fragmentation* as the average *seconds* spent on a single task type or task category (prior to the clinician switching to another task in the workflow) for each observation; this will be referred to as *average duration* for brevity. This concept of *duration* is slightly different from Zheng and colleagues who define their measure as “the average amount of time continuously spent performing a single clinical activity” or *average continuous time* (ACT), and assumes that individual tasks measured were fully completed without interruption.[25] As our TMS took place in a real-world setting, we do not assume that *average duration* among tasks were captured without interruption (see Figure 3).

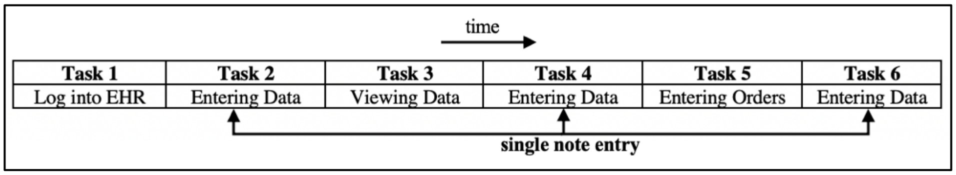


Figure 3. Fictional workflow captured through a time-motion observation depicting a single note entry activity interrupted by data viewing and order entry tasks

We characterized task-switch types as task pairs comprised of two consecutive tasks (that are temporally-related in the workflow) for all task sequences in each of the time-motion observations. For example, a task in the i^{th} position of a sequence of tasks observed within an observation was paired with the task in the $i^{th}+1$ position in the task sequence, the task in the $i^{th}+1$ position was paired with the task in the $i^{th}+2$ position, and so on and so forth. Finally, task involvement in task switches was operationalized as the frequency at which a specific task appears in a sequential task pair (i.e., task-switch type) independent of whether it is in the initiating or the succeeding task position. For instance, Figure 4 depicts a sequence of four consecutive tasks with three task-switch types where *viewing data* is involved in all three of the task-switch types represented.

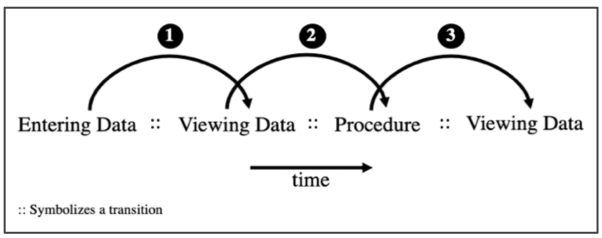


Figure 4. Characterization of task-switch type and task involvement in a sequence of tasks

To understand the impact of particular task-switch types, we propose a measure that focuses on the portion of tasks that account for approximately 80.0% of task switches. This is in accordance with the Pareto Principle which asserts that for many phenomena observed, approximately 80.0% of the effect derive from 20.0% of the causes; by ranking top task-switch types in descending order, insights can be provided for targeted interventions.[26] Based on this principle, we quantified task-switch volume-to-type ratios per clinician role and setting across observations (see Table 2), defined as the proportion of task-switch types that account for the top 80.0% of the rank-frequency distribution. In this metric, larger ratios indicate that fewer task-switch types account for the majority of occurrences per clinician role and setting, and smaller ratios indicate more distributed task-switch types per clinician role and setting. Ranked frequencies of the task-switch types were compared against the Generalized Pareto distribution. All analyses were performed using Python 3.6.

Results

Over 166 hours of time-motion observations are represented in this analysis of APPs (~122hours) and RNs (~44hours), and a total of 13,908 tasks were captured. Of the 47 observations conducted, 34 (72.3%) were APPs and 13 were RNs. Fifteen clinicians were observed in the ACU (n_{APP}=7; n_{RN}=8), 14 in the ICU (n_{APP}=9; n_{RN}=5), three in the ambulatory clinic (n_{APP}=3), and 15 in the ED (n_{APP}=15). Clinicians aged 25-34 years represented the largest proportion of the sampled population in both APP (76.5%) and RN (38.5%) roles, and largely comprised of women (61.8% among APPs and 92.3% among RNs; see Table 1). Overall, clinicians averaged 1.4±0.6 task switches per minute per observation. APPs in both the ACU (1.5±0.70) and ED (1.4±0.6) settings experienced task-switch rates consistent with the overall mean, while APPs in the ambulatory clinic (0.9±0.2) and ICU (1.3±0.5) experienced lower task-switch rates. RNs in the ACU and ICU exhibited task-switch rates that were both higher (1.7±0.5) and lower (1.1±0.3) than the overall clinician mean task-switch rates, respectively (Table 3). On average, average duration on a single task was similar across APPs (43.8±101.7s) and RNs (40.3±146.0s). Average duration was highest among APPs in the ambulatory clinic (66.6±77.9s) and lowest among ACU APPs (40.6±108.3s). Among RNs, those who practiced in the ICU setting had greater average duration (53.4±202.3s) compared to those in the ACU (35.4±117.6s; Table 4).

Table 3. Frequency of task switches per minute stratified by role and setting (fragmentation)

	Advanced Practice Provider				**Registered Nurse**			
Location	**Mean (# switches/min)**	**SD**	**min**	**max**	**Mean (# switches/min)**	**SD**	**min**	**max**
Acute Care	1.5	0.7	0.6	2.3	1.7	0.5	1.2	2.7
Ambulatory	0.9	0.2	0.7	1.1	--	--	--	--
Emergency	1.4	0.6	0.6	2.6	--	--	--	--

Intensive Care	1.3	0.5	0.6	2.2	1.1	0.3	0.8	1.4
Overall Clinician Total	1.4	0.6	0.6	2.6	1.5	0.5	0.8	2.7

Table 4. Average duration on a task stratified by role and practice setting (magnitude of fragmentation)

	Advanced Practice Provider		**Registered Nurse**	
Location	**mean (s)**	**SD**	**mean (s)**	**SD**
Acute Care	40.6	108.3	35.4	117.6
Ambulatory	66.6	77.9	--	--
Emergency	41.7	85.2	--	--
Intensive Care	46.6	129.6	53.4	202.3
Overall Total	43.8	101.7	40.3	146.0

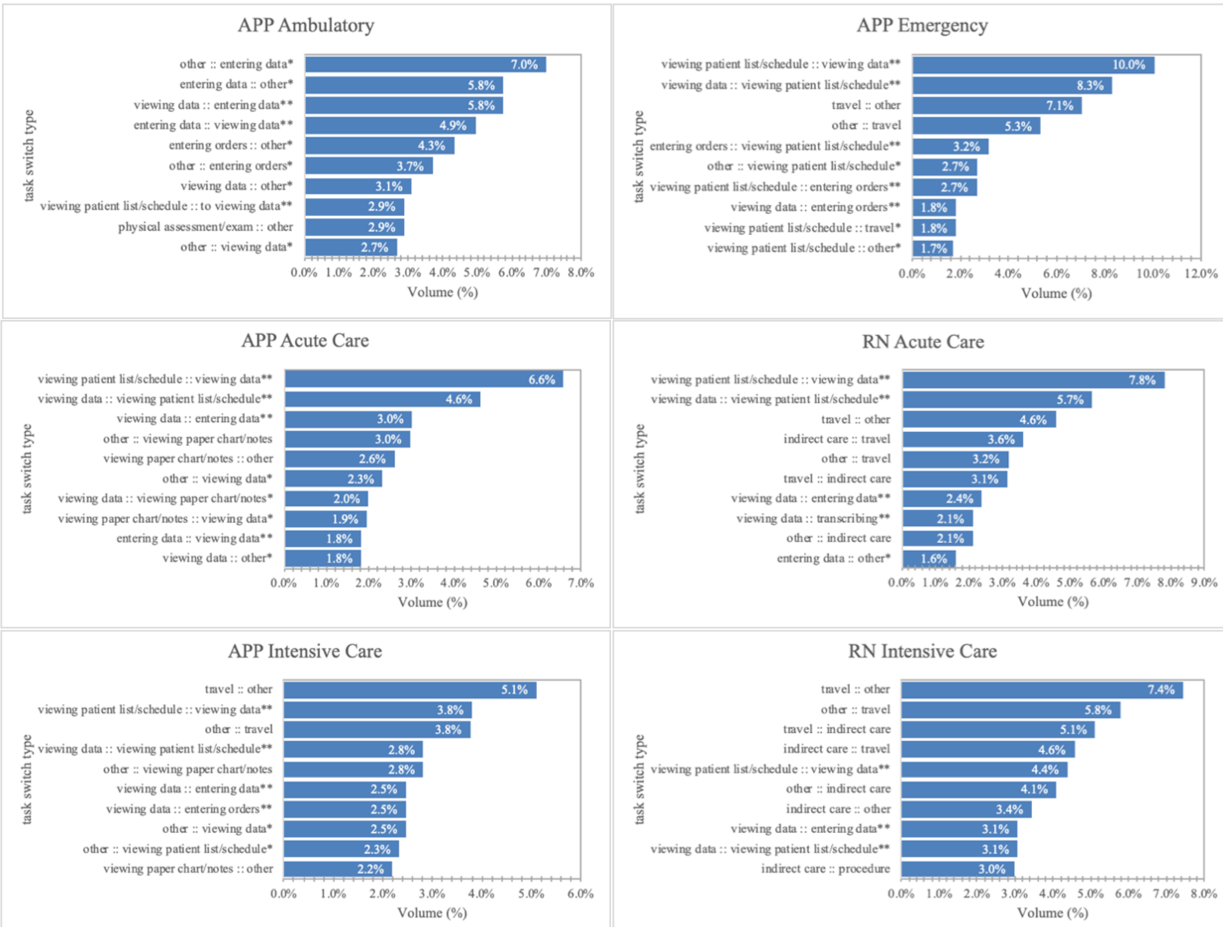
Table 5. Average duration on a single CIS-related task stratified by role and practice setting

	Advanced Practice Provider								**Registered Nurse**			
	Acute Care		**Intensive Care**		**Ambulatory**		**Emergency**		**Acute Care**		**Intensive Care**	
Task	**mean (s)**	**SD**	**mean (s)**	**SD**	**mean (s)**	**SD**	**mean (s)**	**SD**	**mean (s)**	**SD**	**mean (s)**	**SD**
Entering Data	69.0	81.2	67.7	69.1	85.7	115.6	102.4	112.7	62.4	65.2	89.9	98.4
Viewing Data	28.1	37.7	28.2	39.3	55.4	56.6	21.6	29.6	16.7	22.5	44.4	72.9
Documenting Handoff/Sign-out	31.4	29.8	36.8	36.0	--	--	68.3	99.1	7.0	1.0	--	--
Log into EHR	31.5	20.6	31.7	26.5	18.0	28.4	34.4	20.9	22.1	10.3	35.8	32.5
Log out of EHR	--	--	3.3	2.3	3.1	4.1	5.3	7.6	11.0*	n/a	7.0	5.7
Medication Administration	--	--	--	--	--	--	5.0	n/a	68.6	71.2	47.9	63.6
Medication Reconciliation	109.5	128.7	--	--	55.1	63.3	44.1	45.6	109.0*	n/a	--	--
Entering Orders	45.9	45.8	32.2	28.0	74.3	66.4	52.4	48.0	17.3	8.2	28.0	n/a
Viewing Patient List/Schedule	12.4	16.6	13.7	20.5	22.5	20.3	19.6	29.5	7.9	10.9	7.0	6.1
Transcribing	21.1	15.1	25.2	25.9	--	--	24.2	26.8	27.7	34.5	69.5	2.1
Smartphone Clinical Messaging App	23.2	16.5	--	--	--	--	21.4	29.1	25.3	21.4	24.0	16.3
Use of other CIS	29.5	27.2	60.2	52.4	--	--	--	--	28.7	40.6	24.0	29.6
Overall Total	30.3	45.6	32.0	43.3	63.5	82.0	33.4	54.7	26.3	40.8	40.9	67.3

* Potential outlier as only one occurrence observed; standard deviation could not be calculated.

Of the 625 possible task-switch pairs based on the taxonomy (i.e., 25^2 tasks), 429 (68.6%) types were represented in the data. Eighty-four (19.6%) of the 429 task-switch types presented in the data accounted for 80.1% of all switches in the dataset. Of those, *viewing data* (20.5%), *entering data* (7.0%), *entering orders* (3.9%), and *viewing patient list/schedule* (16.8%) were involved in nearly half of all task switches (48.2%); *documenting handoff/sign-out* was not present (0.0%). Accounting for all CIS-related tasks which included *smartphone clinical messaging app* (1.7%), *transcribing* (0.9%), *log into EHR* (0.2%), and *medication administration* (0.4%) added only a marginal increase in the level of task involvement (51.3%); all other CIS-related tasks had no involvement in those task switches. Thirty-six of the 84 task-switch types (42.9%) consisted of switches between CIS-related and non-CIS-related tasks; 28.6% consisted of switching between two CIS-related tasks. Direct care tasks of *physical assessment/exam* (78.4±108.5s), and *procedure* (128.7±281.7s) exhibited longer average durations compared to other tasks and were involved in only 2.5% of all task switches. Average duration among data entry- and data viewing-specific tasks, including *viewing patient list/schedule* (15.7±24.7s), *viewing data* (25.6±37.4s), *documenting handoff/sign-out* (37.9±45.6s), and *entering orders* (48.8±47.3s) were, on average, shorter in average duration with the exception of *entering data* (81.4±94.6s).

Task-switch volume-to-type ratios (TSVR) were approximately 80.0% to 30.0% among all roles and settings excluding APPs in the ambulatory setting (~80.0% to 40.0%) and APPs in the ED setting (~80.0% to 20.0%). This means that overall, 80.0% of all task switches in the average workflow were explained by only 30.0% of all task-switch types represented in the data (i.e., a small subset of switch types account for most of the switching). Variations in the distribution of task-switch types present in the workflow, and frequency at which each occurred, were observed between roles and settings. For example, the TSVRs among APPs were: ACU (80.0% to 31.0% [i.e., 78 of 252 switch types accounted for 80.0% of switches]), ambulatory clinic (80.0% to 40.5% [32/79 types]), ED (80.0% to 18.7% [47/252 types]), ICU (80.0% to 30.0% [68/227 types]). Meanwhile, TSVRs among RNs were: ACU (80.0% to 29.1% [69/237 types]) and ICU (80.1% to 30.9% [50/162 types]). The top ten task-switch types varied across clinicians and settings but *viewing patient list/schedule to viewing data* and *viewing data to entering data* were prevalent across all roles (Figure 5).



*Switch involving one CIS-related task
**Switch involving two CIS-related tasks
::Symbolizes a transition

Figure 5. Proportion of top 10 task-switch types stratified by clinician role and practice setting

In comparison with APPs in all other settings, ED APPs presented the highest average duration for *entering data* (102.4±112.7s), in addition to *documenting handoff/sign-out* (68.3±99.1s) which was double the time APPs spent on the same task in both the ACU and ICU (Range: 31.4-36.8s). Average duration for *viewing data* among ambulatory APPs were twice as long as their APP counterparts (Range: 21.6-28.1s). Average duration of *medication reconciliation* among ACU APPs (109.5±128.7s) was double that of ambulatory and ED APPs (Range: 44.1-55.1s). ICU APPs demonstrated the lowest average duration for *entering orders* (32.2±28.0s), whereas ambulatory APPs had the highest (74.3±66.4s). In general, average duration for *transcribing* was consistent across all APPs (Range: 21.1-25.2s) with the exception of ambulatory APPs where *transcribing* was not observed. The *smartphone clinical messaging app* task was only observed among ACU and ED APPs (Range: 21.4-23.2s), while *use of other CIS* was only observed among ICU (60.2±54.4s) and ACU APPs (29.5±27.2s), with ICU APPs presenting with average durations that were twice as long as those measured among ACU APPs. Contrasting ACU RNs, ICU RNs showed a higher average duration for both *entering data* (ICU: 89.9±98.4s vs. ACU: 62.4±65.2s) and *viewing data* (ICU: 44.4±72.9s vs. ACU: 16.7±22.5s). Additionally, average duration for *transcribing* among ICU RNs (69.5±2.1s) was more than two-fold of that captured in ACU RNs (27.7±34.5s). RNs in both settings had comparable average durations for *viewing patient list/schedule* (ACU: 7.9±10.9s vs. ICU: 7.0±6.1s), *smartphone clinical messaging app* (ACU: 25.3±21.4s vs. ED: 24.0±16.3s), and *use of other CIS* (ACU: 28.7±40.6s vs. ICU: 24.0±29.6s; Table 5).

Discussion

In this primary analysis, we examined clinical workflows with a focus on EHR utilization and fragmentation among 47 clinicians (34 APPs and 13 RNs) in four practice settings: ACU, ICU, ambulatory clinic, and ED, using interprofessional TMS data. Clinicians averaged 1.4 switches per minute, which was similar across APPs in the ACU (1.5 switches/min), ED (1.4 switches/min), and ICU (1.3 switches/min), but higher than rates observed in the ambulatory clinic (0.9 switches/min). Compared to ICU RNs (1.1 switches/min), ACU RNs (1.7 switches/min) exhibited 50.0% higher task-switch rates. In the ACU, RNs engaged in 16.4% more switches per minute than APPs; both RNs and APPs had elevated switch rates compared to clinicians in other settings. Conversely, ICU clinicians experienced lower switch rates compared to other settings; RNs in the ICU had 27.0% lower switch rates compared to ICU APPs. One-fifth of task-switch types accounted for 80.0% of all switches; 71.4% of the types comprised of at least one CIS-related task. Further analysis of task involvement among the 80.0% subset of task-switch types revealed that CIS-related tasks were involved in over 50.0% of all task switches, and that data viewing- and data entering-specific tasks accounted for nearly all of those documented activities.

Unique to previous TMSs, this study comparatively analyzes workflow patterns across APPs and RNs in distinct practice settings through a profession-agnostic taxonomy developed for and employed in the observations (further described in Schwartz et al.[20]). Our use of a single taxonomy to capture workflows and quantify burden across different types of healthcare professionals demonstrated the ability to capture subtle differences across these roles and settings. For example, our workflow quantifiers of fragmentation and magnitude found that while ED APPs presented with the highest average duration for CIS-related tasks, including *entering data* (102.4s) and *documenting handoff/sign-out* (68.3s), ED APPs additionally had higher than average task-switch rates (1.4 switches/min) compared to the average of APP setting means (1.3 switches/min). Prior research has demonstrated that burnout is ubiquitous among particular subspecialties like ED physicians.[28] While research on the transition from locally-developed EHRs to commercial EHRs in ED settings demonstrate no associated increase in time spent on specific tasks, it has shown a significant increase in the frequency of task switches per minute.[29] Therefore, our findings of higher task-switch rates in the ED setting is consistent with the literature and may serve as a marker of documentation burden. These patterns will be crucial to monitor in the post-implementation phase of our TMS.[29]

Evidence has shown that increased cognitive burden and memory costs is correlated with frequent task switching.[30] As mentioned previously, ambulatory APPs were observed with the lowest task-switch rates (0.9 switches/min) as well as the highest average duration for tasks (66.6s)—vastly different compared to all other APP workflow patterns which engaged in approximately 1.4 switches per minute with an average duration for tasks around 40 seconds. Likewise, ambulatory APPs engaged in fewer task-switch categories. These switches were more distributed across many task-switch types (e.g., 32 of 79 types accounted for 80.0% of the task-switch volume), greatly deviating from the Pareto principle (i.e., 80/20 rule). Research has indicated that primary care physician (PCP) workflows not only vary significantly across PCPs, but also within individual physicians.[22] According to Holman et al.,[22] PCP workflows emerge as a result of interactions between physicians and patients addressing personal agendas, which is "a side effect of patient-centered care". It is also worth mentioning that ambulatory APP workflows in our dataset did not involve certain CIS-related tasks: *documenting handoffs/sign-outs*, *medication administration*, *smartphone clinical messaging app use*, *transcribing*, and *use of other CIS*. It would be noteworthy to examine how this time (which is routinely seen among other APPs) is reallocated within the ambulatory APP workflow. As the data suggests, longer average durations are found in *entering data* (85.7s), *entering orders* (74.3s), and *viewing data* (55.4s) compared to other APPs is possibly attributed to the ambulatory workflow of a patient visit. However, it is important to keep in mind that only three observations were conducted in the ambulatory setting. Research among PCPs has also demonstrated significant positive associations between the number of EHR functionalities used and degree of burnout experienced.[31] From a qualitative perspective, it would be worthwhile to assess if clinical documentation burden is experienced differently between ambulatory APPs and APPs in the inpatient setting.

Our findings suggest that ACU RNs have very distinct workflows when assessed against RNs in the ICU. For instance, ACU RNs experienced higher levels (~50.0% more) of workflow fragmentation (based on switch rate) compared to ICU RNs. Average durations among tasks that may be considered particularly burdensome, including *entering data* (89.9s vs. 62.4s), and *data viewing* (44.4s vs. 16.7s) were higher among ICU RNs than ACU RNs, respectively. Furthermore, average duration of *transcribing* among ICU RNs was more than double that of ACU RNs, a potentially clinically significant finding. Given nurses "represent the last line of defense against medication errors in ICUs",[32] systems should be redesigned support these processes.[33] The top two task-switch types represented in the ACU RN workflow were: 1) *viewing patient list/schedule to viewing data* (7.8%), and 2) *viewing data to viewing clinic patient lists/schedule* (5.7%), whereas the top two task-switch types in the ICU RN workflow were: 1) *travel to other* (7.4%), and 2) *other to travel* (5.8%). These observed differences may be in agreement with the existing literature on nursing workflows, which suggest that ACU and ICU nurses (on average) document data points at the same rate, but exhibit differences in nurse-to-patient ratios such that they are lower in ICU settings compared to ACU settings.[34-36] Higher reported nurse-to-patient ratios among ACU RNs may explain the higher frequency of task-switches involving EHR patient lists and schedules (i.e., more task-switching between patient charts using patient lists; Figure 5).

Our analysis of the 80.0% volume of task switches indicated that among all CIS-related tasks involved (51.3%), *entering data* and *viewing data* accounted for 94.0% of those duties. Thus, clinical documentation accounted for the near entirety of CIS-related workload. This finding is in line with Chaiyachati et al. who observed that 43.0% of internal medicine interns' 24-hour shift is spent interacting with the EHR (e.g., documenting);[24] however, Chaiyachati et al. examines time while we explore switches.[24] Tasks explicitly highlighted were *viewing patient list/schedule*, *viewing data* (e.g., within notes, hand-off tables, flowsheets, etc.), *entering orders*, and *entering data* (e.g., progress notes, discharge notes, flowsheets, etc.).[20] Moreover, *viewing patient list/schedule* was interwoven throughout the top ten task switches among all clinician roles (Figure 5). These results are revealing especially through the degree in which *viewing patient list/schedule* defines the clinician workflow, and its potential for unintended adverse consequences related to patient safety.[37] For example, mis-clicking and interruption while toggling through a patient list of names is commonly associated with wrong-patient orders,[9,10,38] and while number of concurrently open electronic patient records in an EHR alone does not significantly reduce wrong-patient orders among physicians,[39] rates of clinical prescribing errors are directly associated with interruptions and multitasking.[40] From the nursing perspective, it is important to note that *viewing patient list/schedule* in both the ACU (7.9s) and ICU (7.0s) practice settings represented the task with the shortest average duration among RNs. Moreover, task switches involving *viewing patient list/schedule* appear twice in the top ten lists of task-switch types among RNs in both settings (ACU: 13.5% and ICU: 7.5%).

By jointly assessing average duration of a single task with workflow fragmentation rates, we accounted for the measurement of tasks that truly require short duration, and tasks that take longer to complete but are prematurely shortened (due to interruptions). However, this method fails to wholly capture the sequential and temporal aspects of workflows. A natural progression to further explore task interruptions is to evaluate task sequence triads to assess the frequency of tasks flanked by two tasks of similar types or categories. This analysis could further describe the nature of the potential interruptions that occurred (if any) among those tasks requiring longer duration and/or more complexity.[38] Zheng et al. described a similar technique as consecutive sequential pattern analysis quantified as an hourly occurrence rate.[25] In addition, it may by worthwhile to explore other proposed workflow analyses techniques such as network visualization and Markov Chains to examine latent workflow patterns embedded in sequential time-motion tasks.[25,41] Lastly, we intend to triangulate these findings with EHR usage log data to further examine time and click navigation patterns among select EHR-specific tasks such as clinical note documentation,[20] and compare them to post-implementation TMS data of our new EHR. Use of these TMS data in future studies will inform how to streamline our EHR workflows to reduce interruptions and task switching post-implementation.

Limitations

This study has several limitations. Intrinsic to all TMSs, variations in taxonomies used (in some instances) limit the capacity to evaluate results across studies of similar design; therefore, researchers must exercise prudence when assessing functional categories to ensure semantic interoperability. However, we note that our taxonomy was developed based on existing taxonomies in the literature for generalizability purposes and the capacity to compare TMS data across health professionals.[20] As statistical significance regarding differences observed between clinician roles and settings was not assessed due to small sample size, no assumptions about the relationships can be made. Moreover, due to small sample size, standard deviations were often wider than the calculated sample means. While we achieved our target of recording twenty-five hours of observation time per role in each setting, there remains some imbalance in the distribution of clinician characteristics and start time, with participants more likely to be younger and female (Table 1), and observations starting in the early mornings or afternoons and on Fridays (Figures 1 & 2). This may be attributable to convenience sampling of participants. Furthermore, start times and duration of observations varied in our study, as well as the number of different providers observed. For example, only three of five ambulatory observations met criteria for inclusion in this analysis (≥2 hours). Nevertheless, the scale of this study is largely within range of other recent TMSs of nurses and physicians.[42] Lastly, as with all studies that require direct observations of participants,[42] TMSs are subject to the Hawthorne effect. These known limitations among all TMSs are outweighed by the uniqueness and richness of this dataset.

Conclusion

Examining clinical workflows is essential for understanding the potential impact of EHRs on efficiency, documentation, cognitive overload, and safety.[8,34,43] However, operationalized measures of clinical documentation burden are still lacking. The results presented in this study provide a glimpse of the ample possibilities for using interprofessional TMS data to identify and quantify one type of documentation burden—workflow fragmentation—as well as to conduct comparative analysis of workflow fragmentation, task sequence types, and task switches across roles and practice settings. Based on our analysis, clinicians experienced 1.4 switches per minute in their workflow. Tasks associated with data viewing and data entry were involved in 48.2% of all task switches, and yet, had average durations ranging from 15.7-34.0s and 48.8-81.4s, respectively. This finding suggests that frequency of interruptions evaluated through task switching may serve as a proxy for measuring one type of documentation burden and may also shed light on targeted interventions for improving EHR usability. Future work will further investigate the nature of task-switch types, sources of workflow fragmentation, and role of multitasking through TMS domains captured in parallel (i.e., communication and physical location).

Acknowledgements

This study was supported by the US National Library of Medicine of the National Institutes of Health (NIH) under the training fellowship award 5T15LM007079, and the National Institute for Nursing Research (NINR) under grant number 1R01NR016941 and 5T32NR007969. We would like to acknowledge all of the observers and providers who contributed to this project.

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