Accepted Manuscript online: 2022-07-05 Article published online: 2022-08-11

Measuring and Maximizing Undivided Attention in the Context of Electronic Health Records

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Appl Clin Inform 2022;13:774–777.

Undivided attention is a clinician's superpower.[1] Often called deep work,[2] being in the flow, or being in the zone—when health professionals are able to perform their responsibilities with full focus and presence,[3] the care itself is safer and the care process is more satisfying to patients and clinicians alike.[4] The opposite of this state is split attention, moments when clinicians lose focus and, as a result, risk missing important incoming data—whether a cue from the patient's body language or tone of voice,[5] a relevant element of the past medical history, or an abnormal test result.

The design of the clinical environment can support or undermine clinicians' ability to provide undivided attention. It is readily apparent when, for example, the environment impedes a physician's ability to listen intently to his/her patient's symptoms, context, and concerns or a pharmacist's ability to perform medication reconciliation without interruption. Yet we currently have no standard metrics for this important state of work. Without such measures, there is no basis to assess current levels of undivided attention or the impact of efforts to increase undivided attention with associated benefits in terms of safety, patient and clinician experience, and other important outcomes.

This commentary identifies two key interactions where undivided attention is both critical and rare—the clinician–patient interaction and the clinician–electronic health record (EHR) interaction. We then propose proxy metrics of undivided attention during these interactions—$ATTN_{PT}$ and $ATTN_{EHR}$ (►Table 1). These metrics, derived from the EHR, can be used for both operational improvements and research, by characterizing the current clinical environment, determining the association between undivided attention and other outcomes, and optimizing the care environment.

Cognitive Overload—a Situation where Undivided Attention is Impeded

Current clinical environments feature two core types of conceptual units during which attention is often broken with frequent multitasking, task switching, and interruptions: the clinician–patient interaction (direct patient contact) and the clinician–EHR interaction (EHR tasks). Breaks in attention within each of these two units increase clinicians' cognitive workload, which in turn contributes to burnout.[6–12] The two interactions impede each other, with EHR tasks and direct patient contact typically overlapping.

With each diversion of our attention from one focus to another, there is an attentional blink, a drop in the data we can take in, that lasts approximately 90 seconds.[4] Misdiagnosis, medication errors, and inappropriate treatment are more likely to occur when the physician or care team member is unable to devote undivided attention to the patient, on the one hand, and, separately, to EHR tasks, on the other.

Undivided Attention for Clinician–Patient Interactions

The natural flow of the diagnostic, therapeutic, and relationship-building conversation between a clinician and a patient can be disrupted by EHR tasks such as signing in, completing required documentation templates, and responding to alerts. For instance, when a clinician attempts to simultaneously

received
April 18, 2022
accepted after revision
June 30, 2022
accepted manuscript online
July 5, 2022

DOI https://doi.org/10.1055/a-1892-1437.
ISSN 1869-0327.

Table 1 Metrics for undivided attention to patient $ATTN_{PT}$ and undivided attention to individual EHR tasks $ATTN_{EHR}$

$ATTN_{PT} = \frac{PSH - EHR_{PSH}}{PSH}$ $ATTN_{PT}$ = Clinician undivided attention to patient during visits/scheduled hours PSH = Patient scheduled hours (from clarity) EHR_{PSH} = Total EHR hours from log-in to log-out during those same PSH (from UAL)* Example: A clinician with 4 hours of patient scheduled time with 1 hour of EHR time during those 4 hours would have $ATTN_{PT} = (4–1)/4 = 0.75 = 75\%$. *UAL data determines EHR time as "inactive" if there is no mouse or keyboard movement for 5 seconds.	$ATTN_{EHR} = \frac{EHR_{TASK} - EHR_{AB}}{EHR_{TASK}}$ $ATTN_{EHR}$ = Clinician undivided attention to individual EHR tasks, i.e., entering orders, viewing archived patient data, or ordering diagnostic tests. EHR_{TASK} = EHR hours on tasks (from UAL*) EHR_{AB} = EHR hours on attentional blinks, including pop-up alerts, electronic inbox messages, mandatory dialog box, or navigation from screen to screen during those same EHR_{TASK} (from UAL $^{+}$) Example: A clinician with 4 hours of EHR time on tasks and half hour with attentional blinks would have $ATTN_{EHR} = (4–0.5)/4 = 0.875 = 87.5\%$. *UAL determines tasks. A task represents a group of individual user actions performed within a certain time frame to accomplish some given clinical function using the EHR. Based on UAL, it is measured as an ordered list of user actions that occur sequentially until two actions are spaced in time by more than a certain cutoff. EHR hours on a task are calculated as the sum of its constitutive action durations. $^{+}$ UAL contains information of alerts, inbox messages, dialog box, narrator, navigator, and tabs of the encounter, note, order, and result, which can be leveraged to determine attentional blinks. EHR hours on attention blinks are calculated as the sum of durations of actions enabling attentional blinks to occur.

listen to a patient and review information in the EHR, cognitive workload is increased, hazards are introduced, and the opportunity for deep work is compromised. In 2012, Benda et al found that the introduction of EHRs into the emergency room led to increased task switching and attention shifts within the patient–physician interaction.[13] Westbrook et al demonstrated that interruptions and multitasking were associated with significantly higher rates of prescribing errors among emergency physicians.[14] Recently, Schneider et al collected observations of emergency department (ED) physicians and nurses in Germany and the United States. They found the average interruption rate per hour was 10.16 and 12.04 in U.S. and German EDs, respectively.[15]

Undivided attention during clinician–patient interactions can be improved by providing dedicated time for EHR tasks separate from the patient interaction or by implementing advanced models of teamwork where upskilled team members perform many of the EHR–tasks, such as order entry and visit note documentation, in real time while the clinician provides undivided attention to the patient.[16]

Undivided Attention for Clinician–Electronic Health Record Interactions

A clinician completing a specific EHR task can likewise be interrupted by other EHR actions such as a pop-up alert, an electronic inbox message, or a mandatory dialog box. A study conducted in acute, intensive, and emergency room settings showed clinicians on average exhibited 1.4 ± 0.6 switches per minute in their EHR workflow.[17] Split attention, as occurs when a clinician must navigate between multiple screens within the EHR, picking up bits of data to store in their short-term memory and then knit them together into a coherent narrative, also contributes to cognitive load.

Cognitive load can be mitigated by improving EHR usability so that, for example, the test results one needs to review to safely choose a new antihypertensive medication are presented on the same screen as the medication order choices. Other approaches that decrease the cognitive load include creating clear, concise displays of all of the patient's information relevant to a particular condition,[18] reducing the number of alerts and decreasing the clutter from low value information.

Electronic Health Record Audit Log Data

EHR audit log data have emerged as a powerful tool to understand and improve the clinical care environment.[19–24] Audit log data make human–EHR interactions explicit, and thus, unobtrusively provide quantifiable tracking of workflows. In a 2020 manuscript, researchers proposed seven core EHR-use metrics,[19] including total EHR time, work outside of work, and time on visit note documentation among others that served to promote EHR design improvements to facilitate the efficiency of EHR use. A growing body of literature uses these and other metrics,[20,22,25–32] thereby demonstrating the feasibility of their implementation and how their use can help inform understanding of efficient practices and improve future EHR design. The 2020 study also proposed a measure of undivided attention in the clinician–patient interaction, specified as the proportion of a clinic session that the physician spent not engaged with the EHR.[19] This represents the outer envelope of time available for undivided attention. Here, we add operational detail by identifying the specifications for this measure within one of the major EHR vendors, Epic.

Granular EHR actions, such as those documented in user action logs (UAL) and clinician efficiency profile (CEP) data, contain information on EHR tasks such as in-basket, orders, notes, and clinical review, as well as interruptions such as pop-up alerts, electronic inbox messages or mandatory dialog boxes. Switches in clinicians' attention as they move rapidly between logging into the EHR, working in the inbox, switching to laboratory review, switching again to medication list and then to problem list, order entry, etc., can also be captured with UAL or CEP.[17,33] In a 2021 study, UAL was leveraged to identify EHR tasks and their complexity profiles.[34] Therefore, UAL and/or CEP provide an excellent opportunity to develop metrics measuring undivided attention in EHR tasks during the clinician–EHR interaction.

►**Table 1** shows our proposed practical metrics: $ATTN_{PT}$ to measure undivided attention given to patients and $ATTN_{EHR}$ to measure undivided attention during EHR tasks. Although the two metrics are proxies and do not measure the absolute amount of undivided attention, they provide a directional signal and can be used for pre- and postcomparisons for operational interventions intended to improve the amount of undivided attention given to patients and EHR tasks and for comparisons across specialties and settings.

Utility of $ATTN_{PT}$ and $ATTN_{EHR}$

Measures of undivided attention created from EHR audit log data can inform a variety of quality improvement activities. For example, approaches to mitigate clinician burnout or improve patient satisfaction could be targeted to redesign the components of the encounter or workflows of EHR tasks where attention is most often interrupted. Measures of undivided attention could also be examined in the context of patient safety, advancing our understanding of contributors to errors.

The interpretation of the metrics should be conducted in the context of specific care settings. For instance, in EDs, workflow interruptions, disruptions, as well as alerts raised by EHRs, often support the timeliness and efficiency of ED operations. Switching attention to emerging problems or acute care needs is an inherent demand in acute care; however, it may break ED physician or nurse's attention and lead to a decreased value of $ATTN_{PT}$ and $ATTN_{EHR}$. In this situation, the interpretation of the metrics needs to establish user actions that represent interruptions and acknowledge that some interruptions, such as an alert regarding a rapidly destabilizing patient in the ED, can advance patient care. These will be critical to frame the interpretation of the measures such that large reductions may not necessarily be considered beneficial.

Multitasking is also prevalent and may be a necessity or even beneficial in certain settings. However, there are also potential hazards for patients and it is draining for clinicians. Thus, a measure that allows assessment of whether or not this is occurring is still useful in the scenarios when there is a goal to reduce multitasking. More broadly, it is important to recognize that our commentary aims to propose metrics that could provide a directional (NOT exact) measure of undivided attention in clinician–patient and clinician–EHR interactions across various settings in an automated way, which relies on EHR audit logs. The metrics will need to be fine-tuned for specific settings and interpreted with relevant caveats in mind. Nonetheless, there is important value in a measure as a starting point—to be used in the context of efforts to reduce interruptions and to prompt ongoing measure improvement.

Limitations with $ATTN_{PT}$ and $ATTN_{EHR}$

EHR log data have advantages in measuring interruptions related to EHR system utilizations; however, they carry challenges in measuring undivided attention. There are various other types of interruptions that can break clinicians' attention in the direct patient care but are not captured by the log data. Those interruptions include but are not limited to verbal interruptions such as another physician updates patient handoff information, a medication request by a nurse, an environment alarm, a pager resuscitation team notification, a knock on the door, a lost document, a technology failure, etc. $ATTN_{PT}$ would not count workflow interruptions beyond EHRs. For instance, workflow interruptions by interprofessional communication have been identified as one of the most prevalent stressors in ED work but would not be captured by $ATTN_{PT}$. ED is a complex, uncertain, high-paced work environment requiring high coordination demands to meet emergent needs and uphold patient flow. Therefore, ED physicians and nurses allocate a large amount of working time to intradepartmental communication with other ED professionals in direct patient care.[15] Although $ATTN_{PT}$ is restricted to interruptions raised by EHR use (EHR_{PSH} in ►**Table 1**), it suggests that the metrics can still provide directional information for pre- and postcomparisons.

$ATTN_{EHR}$ requires defining the full spectrum of EHR tasks, measuring task durations, and establishing which user actions represent interruptions or switches between screens. Although UAL along with informatics approaches provide a potential way to identify EHR tasks, interruptions, and screen switches, and measure their durations, fine granular UAL and advanced approaches are still required to develop more precise metrics to quantify undivided attention in the clinician–EHR interactions.

Conclusion

Defining and then measuring undivided attention in clinician–patient interactions and clinician–EHR tasks offer a new strategy to support achieving the quadruple aim of better health, better care, lower costs, with improved clinician well-being.[16] Doing so could help clinical and administrative leaders reengineer workflows, optimize team composition, and improve task delegation to maximize the amount of undivided attention that patients receive from their physicians and care teams. Measuring undivided attention is a real problem, and applying our proposed metrics in practice would face many challenges. A pilot study, including with survey-based feedback to test the metrics in a specific setting and identify the difficulties and problems, would be very helpful. In addition, the commentary would provide support for an interdisciplinary study, drawing in those from social sciences who focus on ethnography or observations and interviews with those focused on medicine and quantitative studies to capture how divided attention impacts care and the experiences of the clinician and patient.

Protection of Human and Animal Subjects

Not applicable.

Funding

This research was supported, in part, by the National Library of Medicine of the National Institutes of Health, U.S. Department of Health and Human Services under Award Number R01LM012854.

Conflict of Interest

C.A.S. is employed by the American Medical Association. The opinions expressed in this article are those of the author(s) and should not be interpreted as American Medical Association policy.

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