Optimizing Electronic Health Records Through Readability

Rachel V. Ball[1], Dave B. Miller[2], Shaun Wallace[3], Kathlyn Camargo Macias[4], Mahmoud Ibrahim[4], Ernesto Robalino Gonzaga[4], Olga Karasik[4], Dekai R. Rohlsen-Neal[2], Sarah Barrientos[2], Edward A. Ross[4], Abdo Asmar[4], Ashley M. Hughes[5,6], Peter A. Hancock[1], & Ben D. Sawyer[2]

[1]Department of Psychology, University of Central Florida, [2]Department of Industrial Engineering and Management Systems, University of Central Florida, Department of Computer Science, [3]Brown University, [4]Department of Internal Medicine, University of Central Florida, [5]Department of Biomedical and Health Information Sciences, University of Illinois at Chicago, [6] Center of Innovations in Chronic, Complex Healthcare (CINCCH), Edward Hines JR VA Medical Center

Medical professionals engage in an enormous and ever-increasing amount of reading in Electronic Health Records (EHRs), which may have adverse impacts on patient care. Personalized readability formats (PRFs) may help to accelerate reading these records, without training, and without adversely affecting comprehension in this critical task. Using History of Present Illness (HPI) reports written by physicians, we investigated how personalized fonts impacted medical text reading speed and comprehension. Crowd-workers without medical training read a set of eighth-grade level passages in six common fonts to determine their fastest and slowest fonts, which were then used to display a set of HPI reports and accompanying comprehension questions. Results showed that PRFs accelerated reading of medical passages by 15% while maintaining comprehension. This finding suggests that individualized information design like PRFs, and specifically font optimization, may be a straightforward way to optimize EHRs through readability. We see a future in which PRFs may help physicians in reading medical information, and look toward future studies investigating PRF impacts on medical professionals' EHR reading.

INTRODUCTION

Increasing use of various digital interfaces has resulted in the need for a comprehensive reconstruction of operations for human factors and other professionals. When professionals adopt the new technologies that come with these interfaces, there is the issue of new implementations of tasks at the possible expense of precision and efficiency. There are many examples of new systems intended to improve performance actually impairing it in the field of Human-Computer Interaction (HCI) including driving assistance (Mendoza et al., 2011), aviation (Kaber et al., 2002), and gaming (Desurvire et al., 2004). Fairbanks & Caplan (2004) detail a call to action for human factors professionals in the medical field as there is a severe lack of usability testing and poor interface design of equipment and systems used in emergency settings. In these emergency settings, medical professionals do not have the time to figure out how to use their equipment (Fairbanks & Caplan, 2004). This problem can be addressed by proper human factors design and usability testing, as outlined in a seven-step process (Fairbanks & Caplan, 2004). It can be argued that change that negatively impacts workflow is worse than no change at all, especially when change leads to the misconception that previous systems are being improved upon. While in 2021 electronic information systems are much more advanced than they were in 2004, many of the same concerns are still relevant, and EHR systems design is still in need of improvement.

Electronic Health Records (EHRs)

An Electronic Health Record (EHR) is a digitized patient chart including readily accessible information on a patient's medical history, past and current medications, diagnoses, treatment plans, and other information (U.S Department of Health and Human Services, 2019). The EHR was made to replace paper versions of patient charts and keep patient records in a centralized and accessible database.
In the medical community, an estimated 75% of United States hospitals had transitioned to the use of at least a basic Electronic Health Record (EHR) system by 2014 (Adler-Milstein et al., 2015). More than half of hospitals that reported to have EHR systems reported experiencing challenges with their systems such as IT issues, financial issues, or cooperative issues with physicians (Adler-Milstein et al., 2015). This leaves medical practitioners with the task of reworking their record-keeping systems while still maintaining their patients' health. While the transition to EHRs is largely complete at this time, there is still much work to be done in terms of improving the design of such systems which are still often criticized by clinicians.

Effects of EHRs on Physicians

Physicians spend nearly fifty percent of their time working on EHR data entry or other administrative tasks (Sinsky et al., 2016). This runs counter to the goals of medical professionals who aim to spend their time interacting with their patients, not their computers, and the expectations of their patients which is for their caregivers to focus primarily on their health, not on their records. Most EHRs were not designed with time in mind. While these systems are built with the intent of saving time and effort, they have ended up as time-consuming and difficult to navigate. Excessive time spent on such recordkeeping tasks is a great indication that the advancement of medical record keeping is an essential endeavor. With the ever-increasing complexity of modern medicine, accurate record keeping is essential for patient safety.

Physicians enter the practice of medicine to care for their patients, and the demands of record keeping detracts from that goal. This can lead to a lack of motivation among physicians and could be related to higher rates of stress, burnout, and mistakes. Within human factors, performance augmentation is a critical step in alleviating stressors of the operator. When applied in this domain, we have the opportunity to better the lives of physicians as well as patients.

In a series of surveys physicians were asked to rate their stress, burnout, and job satisfaction among other things (Babbott et al., 2014). Physicians reportedly had more stress and less job satisfaction when they worked with a moderate to high usage of electronic medical records (Babbott et al., 2014). Physician's rating usability of the EHR gave it a usability score of 45.9, giving it the grade of F, and were strongly correlated to burnout rates among physicians (Melnick et al., 2019). Physician stress and burnout rates have been found to be highly correlated with high EHR usage (Babbott et al., 2014; Melnick et al., 2019).

The reduction of burnout and stress rates in physicians can be directly influenced by the streamlining of electronic record keeping, allowing physicians to save their time. Since the transition to EHRs, medical practitioners have reported having less face-to-face time with patients, along with higher levels of musculoskeletal pain from attending to these medical documents so often (Hedge & James, 2014).

Asynchronous alerts within EHRs are an important example of an implementation that has been observed to do more harm than good. While initially intended to aid physicians, asynchronous alerts produce information overload for physicians who typically receive many alerts daily, increasing the likelihood of physicians missing crucial information (Murphy et al., 2012). This is only one example of the many risks of poor EHR usability design.

Risks of Poor EHR Usability

Errors made by caregivers can have significant and sometimes fatal consequences. EHRs are intended to help prevent errors, but poor usability can increase error rates. Of patient safety reports that explicitly mentioned EHRs most harm reports were due to EHR challenges with data entry, alerts, and interoperability (Howe et al., 2018). A 1986 study performed by Lakshmanan et al., investigated the cases of patients at the Cleveland Metropolitan General Hospital that were admitted for iatrogenic complications. These cases were defined as due to mistakes made by physicians and/or patients (Lakshmanan, 1986). Nearly fifty percent of iatrogenic diseases observed were described as preventable if detected early enough (Lakshmanan et al., 1986). We hope that improving upon the quality of online medical records can allow for these errors to be caught directly at their source, strengthening the meaning of patient safety along with physician precision.

Improving EHR usability could have a life-saving impact. In a study by Moacdieh and colleagues, participants were asked to read through an EHR and diagnose a simulated patient (Moacdieh et al., 2014). Simulated EHRs that were less dense in terms of layout took physicians less time to read through and physicians were less likely to miss crucial information (Moacdieh et al., 2014). This is a strong indication that EHRs currently lack usability, a flaw that could be detrimental in a high-risk medical setting.

Rather than teaching physicians to be able to work around the inefficient EHR, these systems can be closely examined from a human factors perspective and improved upon to work in conjunction with physicians instead of forcing them to work with disjunction.

Physician-Patient Relationships

Less time spent on EHR usage means more time interacting with patients. Positive relationships between patients and physicians have led to better healthcare for patients, as well as more enjoyable working conditions for physicians (Hall et al., 2002). A study on the effects of interpersonal attraction on physicians and their patients found that liking between physician and patient led to better health reported among patients along with feelings of loyalty and overall satisfaction (Hall et al., 2002). More one-on-one time between physicians and patients can be achieved through a reduction of the time allocated for other, more business-centered, aspects of a physician's occupation. This allows physicians to focus on the part of the job they signed up for – taking care of patient's health and wellbeing.

Taking a Human Factors approach to the integration of the EHR and physician's time and knowledge base allows for a more unified and effective form of patient-based care. Considering a complete redesign of day-to-day activities in the medical community through time-saving on medical records has incredible implications (Hancock, 2018). The medical community has not effectively streamlined the restructuring of time in this manner with record keeping as it has in other medical aspects. Doing so would greatly advance the symbiosis of physicians and patients, along with the meaning of patient safety. Saving time on simple yet necessary tasks is essential to increasing the bandwidth of the medical environment, without compromising care quality. Rather than cutting down time spent on interacting with the patients, effective usage of time dedicated to administrative and medical records tasks will allow patients to receive higher quality and more satisfactory care.

A successful physician-patient encounter is one that properly allocates time in favor of the patient. In order to improve this area, the focus must be placed on "preserving the patient-physician relationship" (Braddock & Snyder, 2005). An increase in EHR usability will allow for proper time allocation and dedication to the needs of the patient. If more time were allocated towards the patient, then trust is built as the physician accomplishes the role as "patient advocate" (Braddock & Snyder, 2005). Thus, modifying how physicians spend their time on administrative tasks directly allows for physicians to place more of their focus on patient care.

Personalized Readability Formats (PRFs) May Help

Increasing legibility has been shown to produce faster reading times and improved recollection among readers. Font changes alone can increase reading quality, improving recall on medical texts. In a 2005 study by Gasser et al., undergraduate participants, who were not considered to be experts in the field, realized a 9% improvement rate on information recall (Gasser et al., 2005). If experts, such as physicians or other persons in the medical field, were examined on related content their reading speed could see a larger improvement since they have a better understanding of medical texts through working in the field. In a more recent study, individuals were able to read 51% faster on average in their individual fastest font as compared to their slowest font (Wallace et al., 2020). Both studies indicate that legibility is highly variable and could greatly enhance reading speed and shorten reading time. Legibility can be used to optimize the efficacy of the EHR system and could potentially lead to increased communication levels and promote trust between patients and their healthcare providers. We expect that legibility changes will increase reading speed levels on non-medical text and on medical text. Furthermore, we also expect that legibility changes will increase comprehension levels on non-medical text and on medical text.

METHODS

Participants

Twenty-five crowd workers on Amazon Mechanical Turk served as non-medically trained participants. Prerequisites for participation in the study were being 18 years of age or older, fluent in English, and having normal or corrected-to-normal vision. Participants were compensated monetarily through the Amazon Mechanical Turk system.

Crowd workers are commonly employed to complete simple, one-time tasks (Ross et al., 2010). Amazon Mechanical Turk (MTurk) is a platform that is able to gather crowd workers as participants at a fast rate and have high participation completion rates (Mortensen & Hughes, 2018). Crowd workers are increasingly becoming a more international group, ensuring participants that are highly variable in areas such as age, ethnicity, and education (Ross et al., 2010).

Procedure

Participants, recruited through the Amazon Mechanical Turk crowd-work system were first presented with a pre-test survey that included questions that prompted participants if they have been diagnosed with a reading disability, and how comfortable and proficient they were in reading text written in English. No demographics data was recorded due to an error in the system.

The study itself contained two stages. The first stage included a reading speed test using six common fonts, following the work of Wallace et al. (2020). A set of non-medical passages written at an eighth-grade reading level were presented, and reading speed was automatically computed by the system. The reading passages were followed by a set of comprehension questions. Participants then read six medical text passages, each detailing a patient being admitted to emergency care and History of Present Illness (HPI) written by internal medicine physicians at UCF for the purpose of this study. Three were presented in the participant’s fastest font and three presented in the participant’s slowest font, as determined by the first stage test. These six passages were presented in a random order.

Each passage was broken into segments of approximately 150 words on each screen, and these were followed by a set of comprehension questions on a separate page to prevent participants from going back to the text. Comprehension questions in the second stage consist of five total questions: two on the first part of the passage, two on the second part of the passage, and one medical diagnosis question. After participants finished reading the passages, they were directed to a post-survey including further demographics questions, if they consciously adjusted their reading speed to influence their comprehension level (much slower than normal to much faster than normal), how much time they spend reading an electronic health record per patient encounter, how well they felt they understood medical text (not at all to nearly completely), and any pain points they experience when reading documents. The study took about 30 minutes to complete. Due to a failure of the survey system, the data from the demographics and self-report questions was not captured.

RESULTS

Participants realized significant gains reading both eighth-grade text and medical text in their fastest font, compared with their slowest font as determined by the font speed test. A repeated measures ANOVA found a highly significant main effect of slowest or fastest font on reading speed, $F(1,24)=40.937$, $p<.001$, $\eta p^2 = .630$. Participants on average read eighth-grade text at a rate of 205 WPM (*SD*=77.61 WPM), but increased their speed by an average of 105 WPM (*SD* = 7.61 WPM) when reading in their fastest font (*M* = 310.12 WPM, *SD* = 112.18 WPM). For medical text, the increase was not as large, participants read medical text on average 40.1 WPM (*SD* = 50.1 WPM) faster in their fastest font (*M* =301.77 WPM, *SD*=118.41 WPM) compared with their slowest (*M*=261.67 WPM, *SD*=90.92 WPM), see tables 1 and 2. Comparing the difference in reading speed in slowest and fastest fonts on non-medical text and medical text showed a significant correlation, $r(24) = .452$, $p = .023$.This indicates that the font optimization that increases reading speed for non-medical text also works for medical text, even for a population of non-experts, see Figure 1. A significant omnibus effect of fastest or slowest font on comprehension was not found.

For reading speed, a highly significant interaction between passage type and slowest or fastest font was also found: $F(1,24)=19.232$, $p<.001$. This shows the varying effectiveness of the manipulation: with simpler text, participants realize greater gains when reading in their fastest font compared to their slowest, compared with those realized when reading medical text.

In their fastest font, participants read eighth-grade text at a mean speed of 310.1 WPM (SD=112.2 WPM) and medical text at a mean speed of 301.8 WPM (SD=118.4 WPM). While the effect size is relatively small, this effect is statistically significant, $F(1,24) = 4.862$, $p = .04$, $\eta p^2 = .168$. There is a high correlation between reading speed for non-medical and medical text in a participant’s fastest font, $r(24) = .862$, $p < .001$. This suggests that the fastest font as determined in reading eighth-grade text in the fastest font test accelerates reading in specialized and more complex text.

A significant main effect of passage type (eighth-grade or medical content) on comprehension was found, $F(1,24) = 7.60$, $p = .01$, $\eta p^2 = .240$. In their fastest font, participants had a mean comprehension level of 92%

(SD=19%) when reading eighth-grade text, and 77% (SD=20%) when reading medical text. These findings indicate that the medical text passages differ in difficulty from the eighth-grade reading passages, and this influences both reading speed and comprehension level, see Figure 2.

Eighth-Grade Non-Medical Text

	Minimum	Maximum	Mean	Std. Deviation
Reading speed in fastest font (WPM)	151.00	598.00	310.12	112.18
Reading speed in slowest font (WPM)	97.50	379.50	205.12	77.61
Reading speed difference (WPM)	25.00	342.00	105.00	81.60
Mean comprehension in fastest font	.50	1.00	.92	.19
Mean comprehension in slowest font	.00	1.00	.88	.26

Table 1. Descriptive statistics for reading speed and comprehension of eighth-grade (non-medical) text. Note that the 105wpm mean difference between worst and best font represents a potential 51.19% increase in reading speed from a personalized readability format based on font alone, in line with the results of Wallace et al. (2020).

Medical Text

	Minimum	Maximum	Mean	Std. Deviation
Reading speed in fastest font (WPM)	117.00	599.83	301.77	118.41
Reading speed in slowest font (WPM)	109.33	484.83	261.67	90.92
Reading speed difference (WPM)	-23.25	190.42	40.10	50.08
Mean comprehension in fastest font	.25	1.00	.77	.20
Mean comprehension in slowest font	.50	1.00	.83	.14
Difference in comprehension	-.50	.33	-.063	.20
Diagnostic question performance in fastest font	.00	1.00	.57	.30
Diagnostic question performance in slowest font	.00	1.00	.45	.29

Table 2. Descriptive statistics for reading speed and comprehension of medical text. Note that the 40.1wpm mean difference between worst and best font represents a potential 15.32% increase in reading speed from a personalized readability format based on font alone.

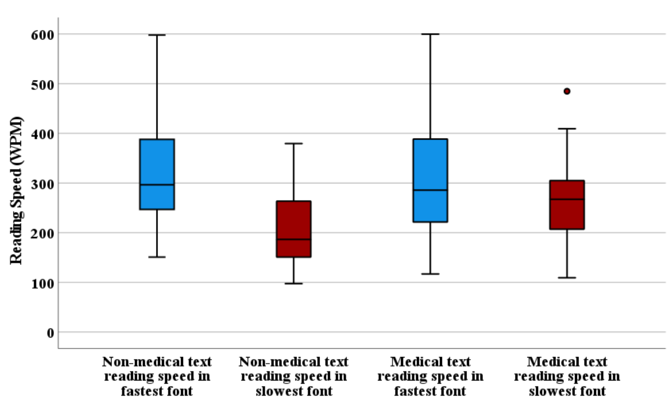

Figure 1. Differences in reading speed by text passage condition. Error bars indicate ±2 SD.

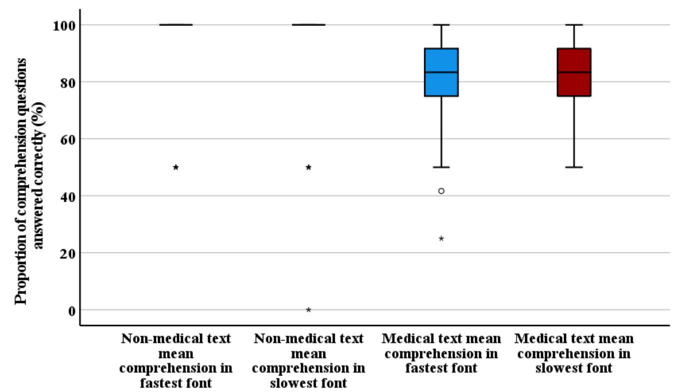

Figure 2. Differences in comprehension by text passage condition. Error bars indicate ±2 SD. Note that non-medical texts are at a ceiling level for comprehension.

DISCUSSION

The present study investigated how reading speed and comprehension in History of Present Illness (HPI) reports such as those present in many Electronic Health Record (EHR) systems can be influenced by selection of a Personalized Readability Format (PRF). Our PRFs, individualized, optimal font selections, in medical text as compared to eighth-grade text, led to significant speed increases. This outcome highlights the time-saving potential of adapting digital reading to the individual. Our results support previous findings showing that a personally selected fastest font can demonstrate great improvements to reading speed (Wallace et al., 2020). This study demonstrates a similar effect for medical text, with participants increasing reading speed while maintaining adequate comprehension.

The high correlation between participants' reading speed in their fastest font with non-medical text and medical text could signify that an individual's fastest font as determined with a short test could be used to optimize reading in multiple domains where text content is more complex. Further research in this area has the promise to unlock the ability to use text optimization to increase reading speed in many areas.

While participants' comprehension of medical text was lower than their comprehension of eighth-grade text, the change was relatively small. This may be due to the fact that participants were non-medically trained and they may have found it difficult to interpret or remember medical jargon. As no significant difference was found between comprehension in slowest and fastest fonts, increased reading speed did not impact comprehension.

In a setting where time is quite valuable, such as in medical caregiver-patient encounters, increasing reading speed without adversely affecting comprehension could provide great benefits. These benefits need to be used wisely, to give back time to the caregiver-patient relationship and not merely increase the pace of clinical care which has been under relentless siege in an effort to increase throughput and medical industry profits. As clinicians are suffering from the demands to do more in less time, in an ever more complex information environment, reducing the burden of reading, as part of an overall effort to improve medical record keeping through optimization of EHRs, will hopefully go far to reduce the stresses of modern medicine.

Limitations and Future Directions

Some limitations of the present study should be noted, and these suggest future directions for research. As due to an error in the software used for this study, demographic information was not properly collected, and thus these factors could not be used as covariates. Reading speeds achieved on the medical text were of similar speed to nonmedical text reading speeds. This may have been due to a small sample size or that participants were nonmedical professionals and may have skimmed the medical texts as a result. Future research will aim to use these factors in the analyses. Also, because electronic health records present a wide variety of data types and can be highly variable, we were only able to replicate a subsection of an EHR (Weiner, 2019). Additionally, we explore legibility in the context of font alone, not varying any other features. Future research could include exploring the improvement of comprehension, as well as other aspects of legibility and how they affect medical documents such as spacing or text size. For example, does increased text size improve comprehension? Does optimizing spacing allow for more seamless visual scanning and improved reading performance?

Studies on the effects of legibility and design of EHR systems may serve as the groundwork for the standardization and regulation of these systems to improve usability. The lack of EHR usability results in serious, and sometimes fatal, consequences (Schulte & Fry, 2019). Standardization of EHR requirements, layouts, and content could provide benefits to caregivers and reduce the risks of error, and future research should continue to develop guidelines for EHR design.

This study provides evidence that personalized changes to increase legibility could improve the reading speed in medical materials, for participants without medical expertise. Future research with medical professionals is planned, to investigate the effect of this intervention for people with substantial domain-specific knowledge. In the future, an examination of legibility in a more naturalistic interface would be necessary. Attaining high fidelity in the context of EHR design and considering time constraints that physicians typically face would allow for a more accurate examination of the ways EHRs are used in a real-time setting.

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