Need for Speed – Towards an AI-based Time-Efficient Clinical Documentation Process

Research-in-Progress

Abstract

Electronic Health Records (EHR) are one of the foundations of digitalization in healthcare and improved the amount of available (digitalized) information about patients. These which can then be utilized not only for patient care (e.g., with decision support systems), but also for research purposes. The digitalized clinical documentation process offers advantages for the healthcare system, despite, it also increases workloads for clinicians, for example through documentation guidelines the clinicians need to adhere to. Hence, the implementation of EHR systems is directly related to perceived stress by clinicians and correlates with a higher number of burnouts in the last decade. In this research-in-progress study, we propose two functionalities that can be provided by artificial intelligence to relieve clinicians in their daily work. Specifically, we focus on the processing of patient histories by clinicians. Utilizing the signal detection theory, we derive hypotheses and lay out the blueprint for a 2x2 online experiment.

Keywords: Healthcare, Documentation Process, Artificial Intelligence, Time

Introduction

In the past decade, EHR has been adopted by a wide range of healthcare institutions across the world. Let alone the US government spent roughly 40 billion dollars in total to promote the implementation of EHR systems across the country (Fierce Healthcare, 2019). The adoption is seen as one of the core pillars of digitalization in healthcare that addresses upcoming challenges the healthcare sector is facing (Berwick, 2002; Mihailescu et al., 2017). By increasing the information quantity and quality, EHR adoption shall ultimately improve patient care. Reduced documentation times, higher information quality through implemented documentation policies, and a reduction of medication errors are some advantages that are commonly mentioned (Campanella et al., 2016; Domaney et al., 2018).

Despite this, many of the promised advantages did not materialize (yet) (Colicchio et al., 2019). On the contrary, EHR adoption in healthcare introduced several unintended consequences for clinicians (Gephart et al., 2015). These unintended consequences result ultimately in increased documentation times for clinicians. For every hour of patient contact, clinicians spend about two hours documenting (Arndt et al., 2017). Apart from the general pressure clinicians face, for example, due to the ongoing COVID-19 pandemic (Sunarti et al., 2021), these increased documentation times add an additional burden. Research suggests that the time spent on documentation processes, often after work hours, induces stress, which is a predictor of burnout (Domaney et al., 2018; Adler-Milstein et al., 2020). Hence, the adoption of EHR is seen as a driver of these burnouts (Tajirian et al., 2020). Tajirian et al. (2020) identify socio-technical and technical reasons for the increased workloads of clinicians. For example, implemented EHR systems often lack usability or enforce guidelines that require additional personnel to enter all additional information for other actors (e.g., legal or billing departments).

Several authors pledge for innovative solutions to restructure EHRs and ultimately support clinicians in clinical documentation processes (Lin et al., 2018; Colicchio et al., 2019). Artificial Intelligence (AI)-based natural language processing (NLP) has the capabilities to classify and potentially restructure patient notes in free texts. The benefits of NLP in healthcare have been demonstrated in various for diseases and disorders, such as neoplasms, cardiovascular diseases, digestive and endocrine, nutritional, and mental disorders (Wang et al., 2018). However, these works are usually focused on the accuracy of algorithms and do not consider the socio-technical system of the clinical documentation process itself. Hence, to address this research gap, we formulate the following research questions:

RQ: How can AI-based information design improve the time efficiency of a clinical documentation process?

Based on the existing literature on clinical documentation processes and the signal detection theory (SDT) (Swets and Green, 1963), we derive a research model to investigate potential AI-based solutions to improve the time efficiency of clinical documentation processes. In our study, we considered the following influencing factors: information structuring and information highlighting. We derived these by synthesizing the current state of clinical documentation. Consequently, we searched for possible AI-based solutions and derive hypotheses about their impact on utilizing SDT.

In the next step, we plan to conduct the proposed 2 (low information structuring, high information structuring) x 2 (low information highlighting, high information highlighting) online experiment. During the experiment, we plan to set the participants into the scenario of supervising an AI-based health information system for documenting and assessing patient notes. This research-in-progress is structured as follows: the relevant theoretical background is examined in section 2. The research design is described in section 3. This is followed by our next steps for conducting the proposed experiment in section 4.

Theoretical Background

Clinical Documentation Processes

With the adoption of the EHR by healthcare providers (e.g., hospitals), paper-based clinical documentation processes were replaced by EHR software that integrates this documentation process. As reported by the Office of the National Coordinator for Health Information Technology, the adoption rate among hospitals is estimated at around 96% and the rate for office-based physicians is around 72% in the US (Office of the National Coordinator for Health Information Technology, 2021). One key argument for the digitalization of healthcare through EHRs was to tackle the upcoming challenges the domain is facing, such as an aging population and, connected to this, chronic diseases that introduce a higher financial burden on the healthcare system (Johansen and van den Bosch, 2017; Panch et al., 2019). Moreover, the system is lacking clinicians in general (World health statistics 2019). Throughout the digitalization of information in healthcare, which is mainly introduced through EHRs, several opportunities such as decision support systems, computerized physician order entry (CPOE), and electronic prescribing are realized (Baumann et al., 2018).

Nevertheless, the rapid adoption also promoted unintended consequences for clinicians (Koopman et al., 2015; Lin et al., 2018; Colicchio et al., 2019; Starren et al., 2021). In general, these unintended consequences foster a cognitive overload of clinicians (Koopman et al., 2015; Colicchio et al., 2019). Through the increased information transparency and guidelines that are provided by EHRs (e.g., through CPOE), clinicians are under pressure to adhere to the demanded information quality. Moreover, multiple studies report that through the utilization of EHRs as a means of communication of multiple actors (e.g., billing section, compliance, and quality improvement), the initial documentation is overloaded with additional information that does not benefit patient care in general (Koopman et al., 2015; Colicchio et al., 2019).

The clinical documentation process involves various steps and is also dependent on the individual domain. However, several activities are a constant part of this process, such as assessing the patient notes and writing and adding additional information. While technologies such as speech recognition revolutionize the activity of generating text because clinicians can speak instead of write (Xiong et al., 2016), it is not a solution for the processing of patients' histories; these are often copied and pasted and, hence, overloaded with unnecessary and outdated information (Siegler and Adelman, 2009).

A possible solution to the problem is intelligent EHR that possibly integrate AI to reduce documentation activities from clinicians to a minimum while maintaining safety and documentation guidelines (Colicchio et al., 2019). However, current research in this domain focuses on the prediction capabilities of AI through EHRs and utilizing the information in EHRs for AI-powered research purposes (e.g., Juhn and Liu, 2020). Moreover, another domain of research related to AI is focusing on explainable AI (XAI), i.e., making decisions of AI algorithms transparent for humans and, thereby, unraveling the black box. While this enables new possibilities for predictive capabilities of AI; it does not reduce the time-consuming process of assessing EHR information and documenting activities. To derive possible solutions to reduce the documentation overload of clinicians, we will consider possible AI-based solutions.

Information Design

In this paper, we will focus on this activity because it is an inherent part of the clinical documentation process. As demonstrated in the previous section, assessing patient notes is a time-consuming but also an important activity for clinicians. We will utilize the SDT, to derive hypotheses about design solutions to improve the time-efficiency of clinicians in this step. In general, the SDT explains the human ability to differentiate between two or more classes of objects (signals and noise) (Klein et al., 1997).

We argue that the laborious process of scanning and processing patient notes is comparable to classical search tasks. Wolfe and Horowitz (2004) define these tasks as settings where an actor looks for a specific object (signal) among other objects (noise), which distracts the searching person and its visual attention; for example, searching for fitting socks in the laundry. Visual attention is defined as a signal that uses “the visual system as a stimulus attribute, excluding other input as noise” (Wolfe and Horowitz, 2004, p. 1). Signal and noise can be distinguished from each other, by color, motion, orientation, and size of objects and is in general dependent on the goal set goal (i.e., What are signals and what is noise?). Moreover, Davies and Parasuraman (1982) visualize the distribution of signals and noise through two overlapping curves. Depending on the human response criterion (xc) and the homogeneity of noise and signals (i.e., the overlapping of these), the human ability to quickly detect signals varies (see Figure 1).

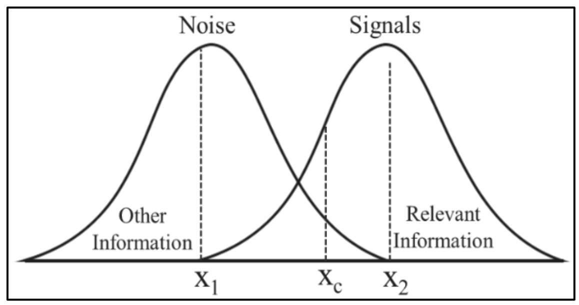

Figure 1. Distribution of Information.

Utilizing the insights from the SDT, we derive the assumption that by manipulating the information of EHRs by visual factors (e.g., color, shape and motion), clinicians could be supported in assessing patient notes and, thus, relieved in their daily tasks. While this redesigning of patient notes would be easy to accomplish if information are stored in a structured and machine-readable format, current statistics suggest that around 70%

Plain Free-Texts	Information Structuring	Information Highlighting
Mrs. Liet 20 yo f, condition constant worsening right lower abdominal pain suddenly started 8-9 h ago w/o precipitating event. Pain is dull, aching, non-radiating, 5/10 on a scale, aggravated by walking, alleviated by Ibuprofen. She denies fever, vomiting, pain in other areas of the abdomen, changes in her urination but reported nausea. She lost some weight, appetite is decreased since last night. Last meal yesterday.	Mrs. Liet 20 yo f, condition constant worsening right lower abdominal pain suddenly started 8-9 h ago w/o precipitating event. Pain is dull, aching, non-radiating, 5/10 on a scale, aggravated by walking, alleviated by Ibuprofen. She denies fever, vomiting, pain in other areas of the abdomen, changes in her urination but reported nausea. She lost some weight, appetite is decreased since last night. Last meal yesterday.	Mrs. Liet 20 yo f, condition constant worsening right lower abdominal pain suddenly started 8-9 h ago w/o precipitating event. Pain is dull, aching, non-radiating, 5/10 on a scale, aggravated by walking, alleviated by Ibuprofen. She denies fever, vomiting, pain in other areas of the abdomen, changes in her urination but reported nausea. She lost some weight, appetite is decreased since last night. Last meal yesterday.

Figure 2. Proposed Manipulations of Patient Notes.

of patient notes are unstructured (Jensen et al., 2017). As stated in the introduction, AI-based NLP has been successfully implemented in several research contexts of healthcare. For example, Henry et al. (2020) trained an NLP model to extract medication and adverse drug events from free texts. Moreover, Zhan et al. (2021), classify medical texts as ICD-10 codes. However, However, current research mostly focuses on the accuracy of the algorithms and not on the requirements and demands from clinicians.

Bringing together the proven technical capabilities of AI-based NLP in healthcare and the theoretical lens of SDT on the clinical documentation process, we derive the following assumption: By reducing the overlapping of relevant information and irrelevant information, the time efficiency of the clinical documentation process will improve for clinicians. To reduce the overlapping, we propose two mechanisms that are derived from the practical problem of (unstructured) medical free-texts and AI-based NLP.

H1: The higher the information structuring of patient notes, the higher the time efficiency of clinical documentation processes.

H2: The higher the highlighting of important information patient notes, the higher the time efficiency of clinical documentation processes.

These mechanisms build on previous research that demonstrated the capabilities of novel algorithms to classify texts and extract relevant information. Information structuring is based on the functionality of text classification of NLP and aims to identify different sections of the text. By doing so, clinicians should be able to faster identify important text sections that correspond to their respective target (i.e., assessing the described family history of the patient). Information highlighting aims to extract single important information from the texts and colors these to help clinicians visually distinguish relevant and irrelevant information.

Research Design

To examine the effects of the two derived information designs on time-efficiency, an online experiment with a 2 (information structuring: low vs high) x 2 (information highlighting: low vs. high) between-subject factorial design and a quantitative follow-up questionnaire is planned (see Table 1).

Table 1. Group Design.

		Information Structuring	
		Low	High
Information Highlighting	Low	**Group 1** Baseline	**Group 2** Information Structuring
	High	**Group 3** Information Highlighting	**Group 4** Information Structuring & Highlighting

The scenario of the experiment is derived from a recent Kaggle challenge (Kaggle, 2022) which aimed at information extraction from clinical patient notes. The participants will be shown several real, anonymized patient notes extracted from the Kaggle dataset. Their task will be to process the information presented and answer questions based on the free texts. The main dependent variable will be the time needed to answer the questions. Additionally, the performance (correct answers) will be measured. The performance allows us to utilize it as an attention check and filter out participants that did not read the free texts properly. Participants will be exclusively clinicians to ensure the external validity of the experiment.

In the example shown below (see Figure 3), a sample patient note and the related questions are depicted. The first manipulation (information structuring) will classify different parts of the text to visualize important and irrelevant information. The second manipulation (information highlighting) will color the text to highlight important information for the clinicians. We plan to analyze the results by conducting a two-factor Analysis of Variance (ANOVA) to identify the impact and potential interaction effects between the manipulations.

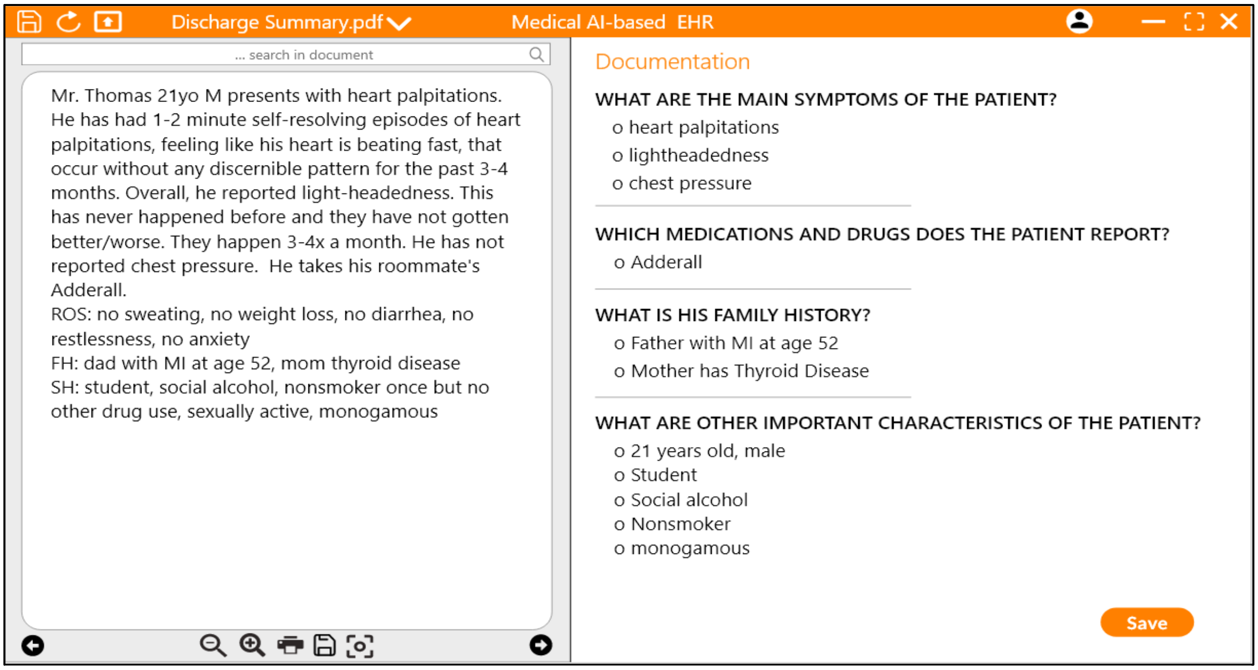

Figure 3. Experimental Scenario (Baseline Group).

Research Continuation and Implications

Our study aims to shed light on the increasing problem of the clinical documentation process for clinicians from the socio-technical perspective of information systems research. With the planned online experiment, we plan to contribute and derive possible impacts on time efficiency and ultimately answer our research question *"How can AI-based information design improve the time efficiency of clinical documentation processes?"*. While many different improvements tackle different aspects of this problem (e.g., speech recognition for text generation), we specifically focus on the analysis and processing of (unstructured) free texts by clinicians, because they are a vital and time-consuming part of the clinical documentation process. The SDT allows us to analyze this process from a visual attention perspective and enables us to derive possible AI-based solutions that could help to relieve clinicians in their daily work. By doing so, our contribution is two-fold. First, we add design knowledge to the clinical documentation process and how AI-based NLP can be utilized to support the workforce. Second, current AI-based experiments mainly focus on human-AI performance (e.g., Fügener et al., 2021; Braun et al., 2022), whereas time has not been considered in human-AI performance so far. Through our experiment, we emphasize the importance of special domains that require tailored solutions for their problems (e.g., healthcare).

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