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Human-Computer Interaction in Electronic Medical Records: from the Perspectives of Physicians and Data Scientists

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Abstract

This study investigated the most common challenges of human computer interaction (HCI) while using electronic medical records (EMR) based on the experience of a large Russian medical research center. Inadequate HCI may have a dramatic effect on the quality of data stored in the electronic medical system. We identified the most common classes of mistakes that emerge because of poor HCI design in EMR. Possible consequences of such mistakes are discussed from clinical and data science perspectives. Integration of specially designed clinical decision support system (CDSS) is considered as a possible way to improve HCI with subsequent increase of the EMR quality. This study is a part of a larger project to develop complex CDSS on cardiovascular disorders for medical research centers.

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1. Introduction and Related work

An electronic medical record (EMR) is a digital version of a case history that contains patient health-related information that has been created, gathered, and managed within one health care organization[1]. The Western world invests significant resources to digitize healthcare with special emphasis on the creation of an integrated EMR to improve the efficiency and quality of health care[2]. EMR offers several key advantages over paper medical records (PMR) related to quality of care, efficiency and high level of patient safety[3].

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Despite this general trend, hospitals in Russia are still using PMR as part of a daily workflow. Moreover, according to the regulations of Ministry of health care of the Russian Federation, physician has just 24 minutes for each patient and in this time physician should not only make their work but also input information in EMR system and put some notes in patient's PMR. When a physician has to choose between spending time filling the EMR and patients' care, he may choose talking with the patient rather than concern about the completeness and accuracy of EMR. Some authors report copy-pasting in medical records which can introduce misleading errors[4,5], and it has been shown that in most cases, this copy-pasting is the result of a heavy workload for physicians[5,6].

Data scientist cannot use obtained data from EMR for further analysis, because of emergence of a large number of errors, typos and entering data into inappropriate fields. Physicians complaint that majority of mistakes arise from lack of understanding of how to interact with the system[7]. Misunderstanding among physicians of the importance of their actions, and a low level of system usability become a barrier for them to be satisfied with EMR[8]. Some physicians may avoid using EMR or use them carelessly[9]. This leads to the decline of the EMR quality.

There are many different kinds of EMR users. Moreover, individual experience affects the outcome of the work for others. We conducted usability studies in order to understand interactions inside our system. The objective of usability studies should reflect the characteristics of the context where the system is being used.

Effective use of EMR requires structured data input; which can be a challenge for users due to EMR method of interaction, that does not match with their mental models and do not meet the requirements of document flow[10, 11]. Poorly designed and cumbersome user interfaces of EMR input data can complicate the structured data-entry that will lead to a deterioration of data quality and incompleteness of data[12]. Consequently, this can lead to suboptimal functioning of information systems of medical technology, integrated into the EMR. An example of such technology is clinical decision support system (CDSS), which is one of the most effective strategies for improving clinical decisions [12,13]. CDSS often requires a large amount of data about the patient (demographic data, data on complaints, symptoms, medical history, physical examination, laboratory and other tests). Despite the fact that the researches aim were improving the quality of service, most of researches reported only about the improvement of the professional performance[13,14] and attempts to identify the critical success factors for CCDS systems have provided conflicting results[13]. CDSS takes the information from forms were filled in EMR and can provide inadequate advice due to incomplete and unstructured EMR data[15].

2. Current Study

This paper presents an ongoing study aimed toward EMR quality assessment and improvement as a part of general conceptual and technological basis for CDSS building[16]. The considered issues appear and are resolved within a scope of optimization for decision making in medicine and healthcare which uses EMR as a core source of information on patients' curation in hospital. This makes the EMR quality improvement to be considered as an important problem for CDSS development.

2.1. Episode Description

For effective work with data for both physician and data analyst, it is necessary to have full information about the episode. This information should include general information (gender, age, height, weight, etc.), anamnesis, information about hereditary diseases, the test results, concomitant diseases, prescriptions and recommendations (including information from other specialists). However, starting from the beginning of the treatment till saving this information to the database, the data undergoes a series of changes and transformations.

At the stage of the patient's inquiry, an ideal description of the episode is being distorted for several reasons. For instance, a patient might misinterpret a question, deliberately conceal some facts from the doctor, forget some of the circumstances or simply do not know certain facts. However, a patient might introduce certain ambiguity to a full set of information. The usual reasons are, for example, an inaccurate indication of medications (time, portion, etc.), when and where the illness started, etc.

At the stage of restructuring and entering of the information into the medical information system (MIS), some changes and alterations appear. Poor human-computer interaction (HCI) or a lack of experience with the system could cause several aggravating errors: information is not entered; information is entered incompletely or in an inappropriate field. Besides, a constant stress of working with the MIS might lead a physician to lose track of survey questions and forget to find out vital details about the patient. Thus, a data analyst usually receives the information about the episode in a distorted form. Therefore, a degree of the distortion affects the final research results.

We assume that by improving the HCI we can, on one hand, reduce the data distortion degree, and on other, improve the interaction with the system and thereby increase the satisfaction of the work for physicians.

2.2. EMR Mistakes

We analyzed **32158** depersonalized EMR of patients referred to a cardiological center due to uncontrolled hypertension (HTN) during a 6-year period (from 2010 to 2015). In the current study, we focused on the analysis of information filled by the treating physician during outpatient visits. Only primary visits records were analyzed. The results of laboratory/instrumental examinations and other external data were compared with analyzed information but were not investigated for mistakes. After the initial data analysis, we selected six classes of the most common mistakes.

Mistakes' classes and frequency of their occurrence were the following:

1) Mistakes in drug prescriptions: (a) typos and (b) brand drug name was written before international nonproprietary name (in **212361 [57%]** of **369417** total prescript drugs and in **31598 [12%]** prescription cases of **261815,** respectively).
2) No blood pressure data (**3283 [11%]** records).
3) No body mass index (BMI) data (**26130 [81%] records**).
4) Diagnosis was not properly structured: it was difficult to retrieve information about the underlying disease, concomitant disease and complications (**20902 [65%]** records)
5) We assume erroneous situation if (a) attached laboratory results of lipids profile were above threshold levels; (b) physician prescripted statins and (c) term "dyslipidemia" was not in the field 'diagnosis'. (In **163 [0.5%]** records)
6) Multiple recording methods of the same information. For example, frequent use of both *"-" and "not complicated*" in the field 'concomitant diseases' (in **16500 [51%]** and **3887 [12%]**) records respectively).

These kinds of mistakes make records unsuitable for analysis, and we can lose important information or medical cases. We assume that ill-designed HCI is one of the leading causes of such mistakes.

From the physician's perspective, these mistakes represent the inaccuracy (unstructured) presentation of important data recommended by guidelines, necessary for a proper examination of the patient and disease. The incomplete case history may result in an underestimation of the severity of the disease or adverse drug interactions, jeopardize the integrity of the information, and lead to mistakes and misdiagnosis, thereby interfering with patient safety or decreasing the quality of health care[17-19].

From the point of view of data scientists, the most important mistakes are those that are connected with missed values (2), even if these missed values can be filled (3, 5). Another issue is disambiguating recording methods for the same things (6) and unstructured fields (4) in records which do not allow retrieving information directly from the record and force data specialists to use such complicated methods as natural language processing (NLP). Due to the fact that the original system was not designed for data analysis and carried out more administrative function, the quality of the data does not conform the entry requirements for analysis. Based on contextual inquiry[20] with data scientists, analysts spend more than 70% of their time creating a knowledge base with consistent, complete, and trustworthy data, but just more than a half of all data can be used.

We used the System Usability Scale (SUS)[21] for the evaluation of usability, this method was developed over 20 years ago and provided a reliable assessment of usability. The result of SUS score is 54%, according to Jeff Sauro research[22]. Such low score along with high amount of mistakes meaning that we should improve usability. For understanding the reasons of this low result we asked open-ended questions, according the answers became clear that users feeling discomfort and have bad experience entering and searching information in the system.

2.3. Integrated Clinical Decision Support

The proper design of EMR GUI is not the only issue for avoidance of mistakes in EMR. Actually, only mistakes of 2-4 classes described in 2.2 could be solved this way. Other mistakes classes needs more intelligent solutions, while the system should provide hints based on previously entered information during the current user session. This task can be solved using CDSS integrated with EMR.

Class 1 mistakes may lead to confuse in drugs purchase that leads to incorrect drug intake [23]. Authors in[24] suggest the list of actions for medical doctors to avoid such situation, so, we assume that the CDSS can help by typos checking with regard to diagnosis and select that typo correction that fits to the diagnosis. Another way to improve drug prescription is to automatically change drug names to use Tall Man lettering, while it can reduce drug name confusion errors[25]. Automated diagnostics of some diseases based on medical test results analysis could help to correct class 4 mistakes.

Multiple recording methods of the same information is a more complicated issue and there are multiple ways to solve it. One way – is recognize current input statement and give autocomplete hint for the user. This hint may be based on most common form for such statements retrieved from EMR. Which way we should select is the topic for future research. The CDSS can perform such tasks as checking possible drug-drug interactions (DDI) in physician prescriptions[26] or checking the consistency of field *'diagnosis'*, medical tests, and prescribed drugs.

In the work[27] authors conducted meta-analysis of several studies on CDSS. Authors mention that modern CDSS should be easy to use, but at the same time, should avoid the possibility of ignoring recommendations in the system. All in all, it is a drastic challenge to develop HCI in CDSS.

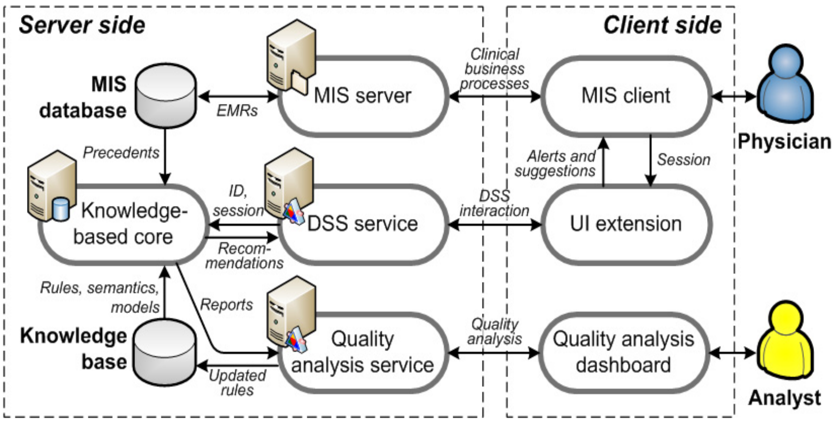

Fig. 1. Conceptual architecture of the CDSS integrated in EMR.

Our current project is dedicated to the development of a CDSS for cardiac diseases integrated with EMR. The first aim of this CDSS is to improve HCI in order to reduce the number of mistakes in EMR. Our system integrates with the currently used EMR (see Fig.1 for conceptual architecture), uses the records stored in EMR, reuses and extends the available EMR user interface (UI). The second allows us to save existing user experience, avoid most mistakes connected with novelty and obtain unbiased estimation of the changes in the healthcare quality. Technical issues of the integration process are solved by the UI extension. That UI extension monitors current user session in EMR, interacts with server side of DSS for session analysis and shows alerts and suggestions when some events are triggered. Currently the proposed architecture is actively being worked out to provide a) the flexible integration with MIS; b) incremental update HCI.

To perform some mistakes correction tasks natural language processing methods should be used and different machine learning and knowledge retrieving methods, including artificial neural network, decision trees and other classification algorithms could be used to create the knowledge-base. Work on this project is still in progress and we are in the early stage of development including the choice of specific algorithms.

2.4. Physicians' and Data Scientists' Participation in the Process of CDSS Development

To improve user interaction of the medical information system, we use the cycle DMAIC (Define, Measure, Analyze, Improve and Control)[28]. Currently we have defined the problem and identified possible causes according to the first phase of the DMAIC cycle. The study was conducted in real contexts and provides rich qualitative data to develop the CDSS and the vision of the future system. In the cycle of Measure-Analyze-Improve, we will make a new version of CDSS. Due to the fact that users invoke the MIS every day, we will apply a method of Subjective Mental Effort Question (SMEQ)[29] for measuring satisfaction on every stage of cycle. A seven-digit scale of responses provides a good balance between the number of options for making an effective choice by the respondent and exceptions error of measurement.

3. Conclusion and Future Works

Completeness and accuracy of data in EMR forms the basis for substantial benefits, including better care and decrease in healthcare costs. The important part of the EMR is the design of HCI. Improvement of human-computer interaction affects far more processes than it might seem at the first glance. Keeping in mind that HCI affects physician adoption of EMR, it also touches the course of treatment, healthcare quality measurement, medical data analysis, and many other aspects that are not covered in this paper. This is the reason why EMR systems should be designed, implemented, and used appropriately. Otherwise, medical systems will result in unintended adverse consequences, such as misdiagnosis, underestimation of disease severity of concomitant diseases or drug-drug interactions. All of this may affect patient safety.

Usage of integrated CDSS aimed at improving HCI provides certain benefits and reduces the number of mistakes in EMR. It also stimulates the adoption of EMR by physicians. These changes should improve the quality of medical care. Good quality of EMR provides data scientists with more data useful for analysis and more confidence about the relevance of the results obtained from EMR data analysis.

Meanwhile, as mentioned above, improvement of human-computer interaction in EMR demands not only technical solutions, but also facilitation of physicians' understanding of the importance of such systems for their routine practice and further use of data stored in such systems. CDSS developers will work closely with physicians and data scientists to understand their needs and difficulties. Therefore, we will conduct ethnographic interviews with physicians, like we did with data scientists, to understand the behavior and rituals of people interacting with the system. We plan to use DMAIC cycle to improve the usability of the system under development.

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