Recent advances of HCI in decision-making tasks for optimized clinical workflows and precision medicine

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Abstract

The ever-increasing amount of biomedical data is enabling new large-scale studies, even though *ad hoc* computational solutions are required. The most recent Machine Learning (ML) and Artificial Intelligence (AI) techniques have been achieving outstanding performance and an important impact in clinical research, aiming at precision medicine as well as improving healthcare workflows. However, the inherent heterogeneity and uncertainty in the healthcare information sources pose new compelling challenges for clinicians in their decision-making tasks. Only the proper combination of AI and human intelligence capabilities, by explicitly taking into account effective and safe interaction paradigms, can permit the delivery of care that outperforms what either can do separately. Therefore, Human-Computer Interaction (HCI) plays a crucial role in the design of software oriented to decision-making in medicine. In this work, we systematically review and discuss several research fields strictly linked to HCI and clinical decision-making, by subdividing the articles into six themes, namely: Interfaces, Visualization, Electronic Health Records, Devices, Usability, and Clinical Decision Support Systems. However, these articles typically present overlaps among the themes, revealing that HCI inter-connects multiple topics.

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With the goal of focusing on HCI and design aspects, the articles under consideration were grouped into four clusters. The advances in AI can effectively support the physicians' cognitive processes, which certainly play a central role in decision-making tasks because the human mental behavior cannot be completely emulated and captured; the human mind might solve a complex problem even without a statistically significant amount of data by relying upon domain knowledge. For this reason, technology must focus on interactive solutions for supporting the physicians effectively in their daily activities, by exploiting their unique knowledge and evidence-based reasoning, as well as improving the various aspects highlighted in this review.

Keywords: Human-Computer Interaction, Decision-making tasks, Clinical workflows, Precision medicine, Physician-centered design

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1. Introduction

Currently, the dramatic increase in the amount of heterogeneous biomedical data is enabling novel large-scale studies, requiring specific and tailored computational solutions. Recently, the latest Machine Learning (ML) techniques have been achieving outstanding performance and an important impact in clinical research [1], ultimately aiming at precision medicine [2] as well as improving healthcare workflows [3].

However, these valuable benefits, ranging from diagnosis to therapy, are accompanied by new compelling challenges. As a matter of fact, this information abundance could overwhelm the analytic capabilities needed by clinicians during their daily decision-making tasks [4]. Indeed, decision-making by healthcare professionals is often complicated by the need to accurately integrate poorly structured, uncertain, and potentially conflicting information from various sources [5]. Healthcare is a critical field involving high risk and time-constrained tasks, characterized by unique peculiarities such as intrinsic intra-/inter-subject variability, harmonization among multiple institutions and legal issues [6]. In these highly specialized and dynamic working environments, the belief that experts cannot fail is another critical point [7], particularly in the clinical practice where professionals with different backgrounds and levels of experience cooperate together [8, 9]. For instance, critical and emergency care requires a well-structured collaboration scheme to deliver safe, timely and effective treatments [10, 11].

In practical scenarios, the ultimate goal is bridging the gap between advanced Artificial Intelligence (AI) methods and healthcare information workflows, also by means of user-centered Clinical Decision Support Systems (CDSSs) [12]. Therefore, the proper combination of AI software and human intelligence capabilities [13], by explicitly taking into account effective and safe interaction paradigms, will permit the delivery of care that outperforms what these two "intelligence types" can do separately [3]. The complexity and lack of usability of sophisticated computational tools might compromise the translation into the clinical environments [14]. Furthermore, the interpretability and explainability issues of the modern AI-based tools [15, 16] must be also considered, since they might further hamper the deployment in the clinical practice [17].

In this context, Human-Computer Interaction (HCI) plays a crucial role in the design of software oriented to decision-making in medicine. CDSSs, Electronic Health Records (EHRs), medical imaging systems, and other computerized tools for collaborative work—such as applications in telemedicine and homecare—are daily exploited by the physicians; indeed, the integration and analysis of data retrieved from EHRs or acquired by wearable devices, remote monitoring, and digital consultations, can deal with the sparse/intermittent data collection and interpretation occurring only during the visits in the clinic [18]. Furthermore, the patient can be directly engaged in the clinical decisions *via* shared decision-making schemes thus allowing for patient-centered healthcare [19].

The inadequate design of Graphical User Interfaces (GUIs) in such systems could generate frustration in the physicians who experience difficulties in the use of computerized technologies. For this reason, the interface design should be inspired by a "physician-centered" approach and then verified by usability testing. CDSSs are often seamlessly integrated with data management and content presentation leveraging AI and Cognitive Informatics (CI) [20]. Interestingly, CI is related to many kinds of applications, in particular the communication patterns in telemedicine, where several clinical teams are involved in data analysis and decision-making tasks.

In this review, we present an overview of many research fields that are strictly linked to both HCI and clinical decision-making: reasoning strategies, Text Mining (TM) and automatic extraction of concepts, AI-enabled devices, collaborative working, patient monitoring, and telemedicine.

Methodology used in the research. The articles included in this review were selected by using the search engines of the main publishers in the scientific literature: Elsevier, Springer, Institute of Electrical and Electronics Engineers (IEEE) Xplore, and Association for Computing Machinery (ACM) Digital Libraries. We further extended the search by exploiting the main public search engines, namely PubMed and Google Scholar; only peer-reviewed articles were taken into consideration. We removed duplicate items and selected the remaining articles in two phases. First, we screened title, keywords and abstract of each article to remove non-pertinent items. Then, we accurately inspected the main content of these articles. Journal articles were considered in the research, whereas some highly relevant proceedings were included during the search refinement. The main search query was "decision-making", further refined with "clinical decision support system" and "interface" to obtain the articles' collection used in this review. The resulting publications were subdivided into six themes, namely: Interfaces, Visualization, EHRs, Devices, Usability, and CDSSs. Consequently, all the arguments are strictly connected to each other and it is possible to comment and discuss the interfaces in decision-making from different points of view. Recent research articles were prioritized, even though the most relevant publications were not excluded in the present review. As a matter of fact, these previous works are often preparatory for fully explaining the rationale underlying the most recent research.

Fig. 1 shows the graph obtained according to the sub-division of the articles

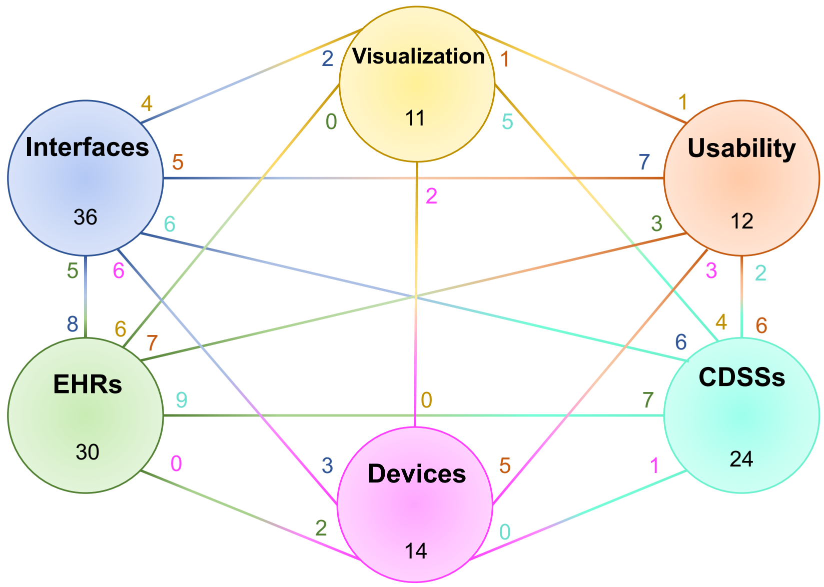

Figure 1: Graph structure representing the analyzed literature articles.

into the six themes with partial overlaps. The nodes represent the main themes (i.e., concepts) identified in our state-of-the-art analysis, showing also the corresponding number of items. The edges denote intersection relationships between the nodes representing the concepts. In particular, the cardinality of the relationships indicates the number of articles belonging to a concept that introduce topics also from another one. For instance, the node pair ⟨Interfaces, Devices⟩ contains 36, and 12 items respectively, while 3 articles regarding Interfaces belong to the concept Devices and 6 regarding Devices belong to the concept Interfaces.

This first classification covered a too broad scope to allow for a unifying concept rather than fragmented topics. Therefore, a careful screening was further performed to tightly focus our study on theories and frameworks for HCI in clinical decision-making, with the goal of drawing conclusions from the achieved empirical findings or usability results. Among the exclusion criteria, we removed those articles that:

- did not deal with human healthcare (e.g., laboratory applications and

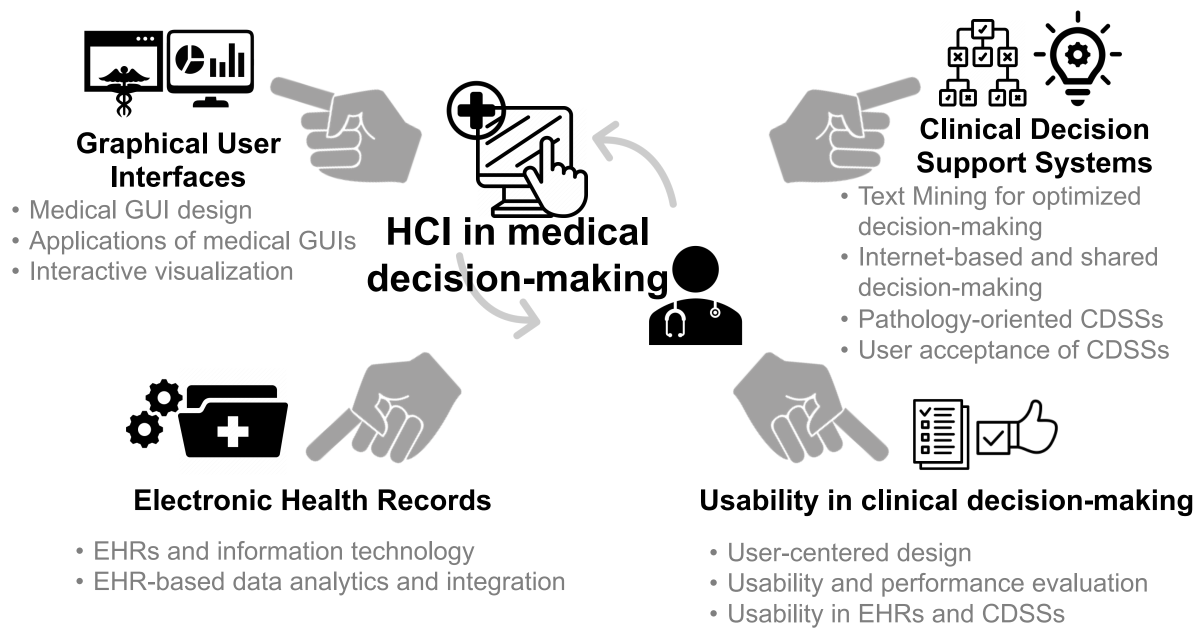

Figure 2: Classification scheme of the recent HCI advances in clinical decision-making tasks. The branches correspond to four clusters of publications, arising from skimming and grouping the six themes in Fig. 1, to direct the focus of this review on HCI and design aspects. Each cluster is described in a different section of this manuscript, while the sub-sections are listed as bullet points.

pre-clinical research);

- were substantially more oriented to technology than design aspects;
- treated predominantly computational methods based on ML or Data Mining to automate clinical decision-making with limited attention to user interaction.

Indeed, wearable and AI-enabled medical devices, even though used in ubiquitous healthcare and continuous patient monitoring [21, 22], offer marginal HCI contributions to decision-making tasks. After these thorough refinement steps, the articles' collection was re-organized by grouping the articles under consideration into four clusters to harmonize the overall description throughout the manuscript.

Considering the results of this detailed analysis, the following four sections of the manuscript reflect the different branches depicted in Fig. 2:

- Section 2 introduces the most important aspects regarding medical GUIs identified during the analysis of the collected papers, with particular focus on the design principles, some relevant applications, and interactive visualization strategies;
- Section 3 describes EHRs as a patient information source that can be processed by cutting-edge information technology, as well as by advanced data analytics and integration techniques;
- Section 4 treats the usability techniques devised for evaluating HCI-based systems from the point of view of user-centered design, together with the corresponding performance evaluation, and their relationship with CDSSs and EHRs;
- Section 5 concludes the literature review, by connecting all the components towards CDSSs for optimizing decision-making tasks by taking into consideration TM techniques, shared decision-making, pathology-specific approaches, and user acceptance issues.

Finally, concluding remarks and considerations are provided in Section 6.

2. Graphical User Interfaces

This section introduces the latest trends in medical GUIs, along with interactive visualization strategies in clinical research and practice. As a matter of fact, GUIs are increasingly playing a fundamental role in the clinical practice, since they represent the actual means of interaction between healthcare stakeholders and the modern computerized solutions. As a matter of fact, mobile computing platforms allow the patient to be involved in a bidirectional interaction along with the physicians [22]. Therefore, new interaction paradigms are required to keep the pace of the cutting-edge technologies in healthcare, and they have to be tailored for the different clinical contexts. In this regard, the authoritative work in [20] points out the fundamental role of CI in developing theories, models and frameworks for HCI in medicine. Both design and applications of medical GUIs are presented.

2.1. Medical GUI design

Cognitive aspects must be explicitly taken into account for an effective GUI design. The work in [23] established that a multimodal interface was able to reveal the human cognition state during ML-based data analytics-driven decision. Human cognition could help to understand how the user accepts the new technologies and, on the other side, the ML models can be modified by taking into account such considerations. Savoy *et al.* [24] analyzed the Primary Care Providers (PCPs) experience with health information technology for the referral process. A PCP has to deal with chats, EHRs, and other information sources. The study concluded that the current GUIs are not adequate to support the information exchange, communication or care coordination for this task. As a consequence, a Cognitive System Engineering (CSE) design was devised in [25], allowing the GUI to support the physician in referral communications. A usability test was performed on two GUIs to compare them by recruiting 30 physicians for the evaluation. Along with CI techniques, the design of computer-based documentation tools should be based on the healthcare providers' perceptions of clinical documentation methods. In [26], the cognitive factors underlying such perceptions were identified by performing a qualitative analysis by means of interviews involving a sample of healthcare providers who used a variety of documentation methods. Five factors influencing satisfaction with clinical documentation tools were identified: document system time efficiency, availability, expressivity, structure, and quality.

In highly dynamic and time-constrained circumstances, appropriate Knowledge Management techniques are valuable. The authors of [27] considered the Asian Productivity Organization (APO) model. Among the 26 Knowledge Management tools, 12 were found suitable for hospital settings. The authors of [28] faced a situation in which the information is uncertain or inconsistent and might be located in a distributed environment, hindering the fusion into a unique knowledge base. A multi-agent framework was devised to solve this problem in dementia diagnosis. As a further step, Knowledge Representation models, based on ontologies or automated reasoning engines, can be effectively exploited to solve complex tasks involved in clinical decision-making. The work in [29] addressed the problem of updating medical classification schemes and ontologies (ICD-9-CM, MeSH, NCIt, and SNOMED CT) with a two-phase approach: (*i*) identification of concepts that need a revision by using an ML approach, and (*ii*) proposal of the type of revision. In particular, for the second phase, the system determines when it is necessary to add or remove concepts or modify the item description. The work in [30] dealt with the imaging biomarkers, which refer to radiological measurements evaluating the therapeutic responses and the early diagnosis of pathologies. Indeed, in the clinical practice features, such as tumor volume and lesions' number, are very important. As a consequence, a particular biomedical ontology was developed, called Imaging Biomarker Ontology (IBO), and exploited existing biomedical ontologies. The work in [31] faced the problem of information movement between health system providers. Indeed, there are neither methods of information interchange nor inventories of system-level electronic health information flows. An ontological model—based on the language Protégé 4—taking into account concepts like diversity, volume, standardization, and connectivity was developed. In such massively distributed and cloud computing environments, the frameworks for scalable distributed computing Hadoop and MapReduce were used in [32] to accomplish Ontology Quality Assurance (OQA). More specifically, the implemented OQA was applied to the SNOMED CT collection. The authors of [33] developed a CDSS for Intensive Care Units (ICUs), called icuARM, which was based on Association Rule Mining (ARM). The CDSS icuARM was built with multiple association rules and an easy-to-use GUI for care providers to perform real-time analyses in the ICU setting.

2.2. Applications of medical GUIs

GUIs are pervasive and guide the interaction between physicians and patients from the diagnosis to therapy in all clinical scenarios. With regard to cardiology, several interesting applications exist. Heart auscultation is the first step for the assessment of a cardiovascular disease. In [34], the phonogram (i.e., a curve representing the heart sound) was considered, by proposing an interactive ML framework for the classification of heart sounds. Furthermore, computerized 12-lead Electrocardiogram (ECG) devices provide an automatic diagnosis, but a wrong one could negatively influence the decision-making process. In [35], a study assessed the diagnostic accuracy in presence of correct/incorrect diagnosis proposal. The analysis concluded that automatic diagnostic proposals affect the accuracy of ECG interpretations. As a matter of fact, 12-lead ECGs might be often incorrectly interpreted: physicians provide their diagnosis considering their first impression. On the other hand, all the ECG devices automatically print out a diagnosis without any interaction with the physician that might lead to a correct interpretation. To this purpose, in [36], the ECG is segmented into its peculiar parts that are displayed on multiple separate GUIs so that the physician is supported during the decision-making task. Exploiting the increasing computational resources, simulators can be useful in clinic. The authors of [37] developed a cardiovascular simulator, which is a computer application reproducing the patient condition, where a physician can test a therapy. Moreover, it could be useful to train specialists in dealing with various diseases. As regards cardiological applications, a digitally simulated patient (i.e., avatar) was used in [38] to verify the ability of the primary care physicians to recognize depressive disorders by means of a conversational task. Kahol *et al.* [39] added a layer of cognitive exercises into simulators for laparoscopic surgery, which are usually exploited for refining surgeons' psychomotor abilities. This methodology was evaluated by two pilot studies.

The growing diffusion of mobile platforms can be exploited for patient empowerment and monitoring. In [40], the authors discovered novel design principles for health Behavioral Change Support Systems (BCSSs), which are mobile apps aimed to change the lifestyle of chronic patients. The study was based on the analysis of the online diabetes patient reviews regarding mobile applications about this disease. Regarding diagnostic applications, the authors of [41] experimentally assessed cases of hematuria by means of photos *via* the instant messaging service WhatsApp Messenger (WhatsApp Inc., Mountain View, CA, USA). The study concluded that the hematuria evaluation with this method is possible and reduces costs of medical service and it can be used in rural and deprived areas. In [42], a new ML method was presented for the diagnosis of depression. It integrates data from smartphone and wearable devices, like the Fitbit wristband (Fitbit Inc., San Francisco, CA, USA) to monitor the heart rate and self reports. The Just-in-Time Adaptive Interventions (JITAIs) in mobile health is increasing interest in the scientific community. Usually, they are reminders and notifications allowing the user to make healthy decisions. The authors of [43] conducted an empirical study to evaluate the interaction between patients affected by hypertension and a mobile healthcare system called iHearth, which is aimed at monitoring this category of chronic patients. In these scenario, the best way to deliver the notifications is during time risk, but there is a constraint to limit these messages because the user could be overburdened. In [44] an algorithm, called Sequential Risk Sampling (SeqRTS), was developed to distribute notifications in a uniform way across all risk times. With reference to homecare, the work in [45] addressed the Personal Health Information Management (PHIM) practices, by sharing the information with the medical staff, in informal care-giving for patients with/without dementia.

Considering the huge amount of patient data, convenient and context-aware presentation of the EHR contents is essential. A "smart forms" system was developed in [46] to improve the information contained in patient EHR. The form resulted to be complete from the medical point of view, even though the usability study revealed that the first version of the GUI was exhibiting several issues (e.g., too detailed lists of symptoms, difficulties in recognizing navigation links, disturbing background/foreground color contrast), which were then fixed in the final version of the GUI. The integration with other forms of data is certainly valuable, such as in the case of clinical applications including patient's genetic profile for a personalized therapy as it is reported in [47]. The authors of [48] performed the integration of a mobile application into a standard EHR for data reading/writing. A small usability study on a patient decision support was also reported regarding the Prostate Specific Antigen (PSA) testing for prostate cancer screening. The principal hurdles encountered in the integration concerned the proprietary EHR vendor Application Programming Interfaces (APIs). The latest Natural Language Processing (NLP) techniques can infer the semantics from text and showed potential in improving the GUIs [49]. In [50], an NLP system was devised by a Recurrent Neural Network (RNN) that was trained to extract events from cardiology medical reports written in Italian. A text *corpus* of 75 reports was annotated and 4365 relevant events and their attributes were recognized. The paper also provided the annotation guideline. The trained RNN was integrated into an NLP pipeline making use of a dictionary lookup approach to identify important concepts found in the text. In [51], an EHR interface was powered by NLP techniques, exploiting MetaMap, as a decision-making support for stroke patients candidate to Intravenous Thrombolytic Therapy (IVT). The authors of [52] presented a process to create highly structured and realistic synthetic patient data and the evaluation of three prototypes was also shown to demonstrate the effectiveness of such a procedure.

In the clinical routine, diagnostic decisions strongly rely upon medical imaging systems, which provide relevant insights into each clinical scenario. However, medical imaging software GUIs typically display a variety of advanced analysis tools, giving rise to a 'tool clutter' situation. Jorritsma *et al.* in [53] aimed at evaluating the usefulness of adaptive customization support in a natural work environment, with particular interest to Picture Archiving and Communication System (PACS) platforms in Radiology [54]. This adaptive customization support would be a useful extension to the standard adaptable PACS interface, since this feature allows radiologists to effectively customize their interface. In [55], the authors proposed a technique that makes use of the Digital Imaging and COmmunications in Medicine standard (DICOM) for data-driven GUI generation, referring to the examined body part, and imaging modality as well as to the medical image analysis task to be performed. In this way, the self-configuring GUI is generated on-the-fly, so that just specific functionalities are displayed according to the current clinical scenario. The feasibility and the effectiveness of the proposed approach was shown *via* a plug-in for the OsiriX DICOM viewer (Pixmeo SARL, Bernex, Geneva, Switzerland). Regarding burned-in protected health information in DICOM files, automatic detection and classification of the text content in the pixel data, aiming at anonymizing the patient information, was performed in [56]. In this way, the patient information must be obtained only from EHRs also in the case of cloud-based medical image sharing for collaborative diagnosis and consultation [57]. Aselmaa *et al.* in [58] incorporated sense-making support within the design of health information systems, by considering the tumor contouring clinical task for radiotherapy planning as a case study. The proposed approach was beneficial for gaining an in-depth understanding of the sense-making process during this critical task, as well as for identifying design requirements for better sense-making support. In [59], Deep Learning (DL) techniques were exploited to generate a diagnosis as textual representation from a frontal X-Ray image. Moreover, realistic X-Ray images related to the nearest alternative diagnosis were generated.

2.3. Interactive visualization

The enormous amount of data in scientific research, particularly in life sciences, is an ideal benchmark for the recent developments in ML and AI techniques. However, new challenges arise from these scenarios, such as model interpretability and explainability [60]. The design of interactive solutions for clinical data interpretation requires the effective integration of medical expertise and data/model visualization strategies [17, 61].

An interactive dashboard for Emergency Departments (EDs) to manage each single patient as well as the entire department workflow was proposed in [62]. Indeed, in emergency care, the clinicians must make just-in-time decisions rather than planning therapy. Recently, in [63], a clinician dashboard to facilitate shared decision-making between patients and physicians was presented. The dashboard provided an easy and intuitive GUI that focuses the patient and the clinician on the patient health problems to allow for a mutual discussion. The GUI showed the patient progress on different aspects of his/her condition (e.g., sleep, pain level). Detailed information can be obtained by clicking on the screen for each aspect of the patient's condition. In [64], an interactive visualization method consisting of two steps was presented. The former consisted in a current regression model by using the R statistical environment to assess important factors of therapy and prescription patterns. In the latter, an interactive dashboard was used with different visualization modalities, and the results of the first step were displayed by means of the Tableau software. Chronic disease patients can have a better comprehension of their illness by means of clinical data augmented with contextual ones but the current applications do not allow the interpretation of multiple data streams.

3. Electronic Health Records

An EHR can be defined as an organized collection of electronic health information regarding a single patient or a large group of individuals. It is a digital data structure that can be updated and shared among network-connected information systems. These records can contain several data formats, such as structured/unstructured text (e.g., personal statistics, medical history, test results) and pictorial data regarding medical imaging scans [65]. Although in the literature the term Electronic Medical Record (EMR) is used interchangeably with EHR, they refer to different information models. More specifically, EMR is a record created in the hospital information system or ambulatory environment, which can be included into the EHR [66, 67]. For the sake of clarity, also Personal Health Record (PHR) has to be mentioned, which is an electronic application for the patient aimed at managing personal medical data that can be made available to health providers [68]. The systems mentioned above could effectively mediate the communication between the physician and the patient, and the proper design of the computer tools can allow for patient's comprehension of medical problems [69].

3.1. EHRs and information technology

EHRs represent a valuable source of patient information and clinical information collected during the healthcare events, *via* Biomedical Informatics. Along with traditional epidemiologic investigations, the functionalities of EHRs allow for population health research by exploiting large-scale and generalizable medical data sets [70]. Towards continuous care, the integration of EHRs with the emerging technologies—allowing for social/behavior measurements—might improve the delivery of healthcare services. However, specific computational solutions must be devised to perform patient data analytics and Information Retrieval, while carefully considering data sharing and privacy [71]. In [72], the authors presented a study on the evaluation of a system to create hospital progress notes using voice and EHR integration to determine whether note timeliness, quality, and physician satisfaction were improved. A randomized controlled trial was conducted to measure the effects of this new method of writing inpatient progress notes, which evolved over time. Intervention and control subjects created 1852 notes, with no significant difference in physician satisfaction or note quality between intervention and control. Even though the authors did not claim the superiority of Voice-Generated Enhanced Electronic Note System (VGEENS) for their primary outcomes, they observed that notes created using voice during or soon after rounds were available within 10 minutes. Importantly, there is also a critical need to validate and translate prediction models that support clinical decision-making in hospitals. The purpose of the work in [73] was to explore a combined data-driven and practice-based approach to identify risk factors associated with hospital-acquired falls. The authors conducted an observational case-control study of EHR data from 14 medical-surgical units of a tertiary referral teaching hospital. The results confirmed the significance of a set of valid fall risk factors and identified a set of new risk factors.

The rapid growth and acceptance of EHRs, and their related standards to exchange information, are improving various aspects of both health practices and patient care. In [74], the authors explored and critically analyzed Health Level 7 (HL7) Fast Health Interoperability Resources (FHIRs) to design and prototype an interoperable mobile PHR that conforms to the HL7 PHR Functional Model and allows for bi-directional communication with OpenEMR, i.e., an open-source EHR compatible with FHIR. The authors prototyped a mobile PHR to demonstrate the capability of HL7 FHIR and its features (i.e., profile, extensions, and capability standard) to design and implement an interoperable PHR. In the study presented in [75], several open-source EMR software packages based on multi-criteria decision-making were evaluated. A hands-on study was performed and a set of open-source EMR software packages were examined. The authors used several evaluation measures while the systems were selected according to a set of metric outcomes by integrating the Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity of Ideal Solution (TOPSIS) models. The GNUmed and OpenEMR software packages outperformed the other open-source packages in terms of ranking score records. However, the study revealed the lack of several features, most notably security, interoperability, and support from developers.

EHRs revolutionized how care providers interact with patient health information, even though the EHR role in collection and retrieval of psychosocial information is not fully well-established. In [76], the authors designed a qualitative study using semi-structured interviews with 17 physicians to investigate their perspectives on the impact of EHR for collecting psycho-social information in the context of care decisions for Type II diabetes outpatients. The authors stated that psycho-social information is perceived as dissimilar from other clinical information, such as glycated hemoglobin (i.e., HbA1c) and prescribed medications. Furthermore, EHRs could impair the collection of psycho-social information because the design of EHR tools makes it difficult to document, search for, and retrieve it. On this line, the study proposed in [77] resulted in identifying seven types of Patient-related Information Problems (PIPs) that patient-care teams encounter during morning rounds. Since PIPs exist in EHR systems, paper documents, and verbal conversations, the study identifies a set of PIPs and how they were being detected and effectively managed. The goal of the study in [78] was to define practice-based clinical pathways for Chronic Kidney Disease (CKD), which is a progressive illness leading to the End-Stage Renal Disease (ESRD). In order to achieve this goal, the system integrated healthcare and domain knowledge, including representation of multidimensional and longitudinal EHR data, identification of distinct patient sub-groups, and extraction of common treatment patterns as candidate clinical pathways. Medical experts can interact with the system by making modifications and redesign while completing the process. Lastly, a visualization layer displays the pathways either for practice review or to engage patients in shared decision-making.

User-centered design can be also valuable in EHR-based computerized applications. In [79], the project Health Design was presented, which employs a user-centered design approach to develop designs and prototypes of computer applications based on PHRs for patients with a wide range of ages. Accordingly, clinicians might create their own tool to mitigate the inadequacy of health information technology. In [80], the design process of an information tool for care coordination was guided by the end-users (i.e., nurse coordinators).

3.2. EHR-based data analytics and integration

Considerable effort has been devoted to effective techniques that analyze and integrate the data extracted from EHRs. In particular, EHR-powered solutions, with characteristics and functionalities adapted for managing particular diseases, are often integrated with CDSSs. Horta *et al.* in [81] presented a CDSS for the co-management of surgical patients in the post-operative ward setting. The data source was a collection of EHRs of patients where the diseases were classified with ICD-9 codes. The study in [82] investigated the most common challenges of HCI while using EHRs, with particular interest on cardiovascular diseases. Inadequate interaction may dramatically impact the quality of data stored in EHRs. Considering medical research centers, the authors identified the most common classes of mistakes mainly attributable to poor HCI design in EHRs: the integration of specialized CDSSs was considered as a possible solution to increase both HCI and EHR quality. In [83], an NLP-powered pipeline for the analysis of German narrative clinical notes on colorectal cancer was developed to retrieve specific guideline-based patient information and annotate it using terms of the Unified Medical Language System (UMLS) for further evaluation by the physician. In order to prepare a high-value research data set, the authors of [84] developed a scalable EHR processing pipeline for managing and editing EHR data from adult ICUs. EHRs are also crucial in shared decision-making, as it is reported in the work of Wang *et al.* in [85] (better described in Section 5).

EDs are certainly among the most critical divisions in healthcare organizations. For this reason, EHRs play a fundamental role for clinical decision-making in such a context by supporting fast and accurate diagnosis, as well as avoiding overcrowding in the hospital ward. Furthermore, a proper data collection of clinical scenarios may enable the development of predictive models and algorithms. In [86], the authors evaluated the usability of software prototypes developed for tablet PCs in an ED. The goal was to keep patient EHRs errorless and accessible *via* mobile technologies. Two alternative prototypes were developed: Mobile Emergency Department Software (MEDS) and Mobile Emergency Department Software Iconic (MEDSI). A case study of 32 potential users of the proposed prototypes at the ED of Kadikoy-AHG, Istanbul, Turkey, was also presented. Usability results confirm that the solution with iconic GUIs (i.e., MEDSI) received better feedback than non-iconic GUIs in terms of Nielsen's heuristic evaluation, effectiveness, and user satisfaction. In [87], a simulated ED environment was developed at the Israel Center for Medical Simulation. Four different actors were trained to simulate four specific complaints and behaviors. The performance of 26 volunteer ED physicians were observed. The study confirmed that EHR access and use in the ED affect the process of medical decision-making by enabling more accurate diagnoses improving patient care and enabling savings in time and money. The study proposed in [88] assessed the performance of different classes of information individually, as well as in combination, in predicting ED revisits. As an increasing number of public data sources exist to describe social determinant of health factors, the authors compared the performance of Two-Class Boosted Decision Trees ML algorithm using 5 classes of information, namely: 1) social determinants of health measures only, 2) current visit EHR information only, 3) current and historical EHR information, 4) Health Information Exchange (HIE) information only, and 5) all available information combined. The results showed that combining all information classes outperformed the models considering separately the information classes in terms of Area Uunder the Curve (AUC). Finally, a different, yet important, aspect of an ED was analyzed in [89]. Since ED overcrowding is a serious issue for hospitals, the authors used TM methods to process data from early ED patient records using the Subjective, Objective, Assessment, and Plan (SOAP) framework, as well as predict future hospitalizations and discharges. Unigrams, bigrams and trigrams were tested for feature formation. In the prediction module, eight TM methods were tested, and a nu-SVM was the best performer.

4. Usability in clinical decision-making

Usability is essential to allow the users to carry out their own decision-making tasks safely, effectively, efficiently, and enjoyably. As a matter of fact, methodological approaches for usability engineering and cognitive task analysis have to be considered in health information systems [90], such as EHRs and CDSSs.

4.1. User-centered design

An accurate analysis of the medical decision-making processes is needed during the design cycle of medical systems. In [91], a cognitive design methodology was presented in the case of different end-users who were instructed with basic knowledge of the healthcare processes. Successively, they had to analyze several scenarios characterized by a medical error event involving healthcare professionals and medical devices. Finally, *via* the think-aloud technique, the users were asked to reflect on the error presence to elicit guidelines useful for the design of safe devices by identifying the modifiable entities to improve each workflow. The work in [92] presented a novel usability procedure for assessing medical devices in terms of patient safety. Heuristic evaluation—a usability inspection method commonly used for software usability evaluation—was modified and extended for medical devices and in particular the infusion pumps. During a heuristic evaluation, experts underwent a walk-through evaluation of the interface, by identifying the elements that violate usability heuristics. The key idea of the work was that it is possible to obtain a good assessment of the intrinsic safety of a medical device by analyzing the issues related to the "interaction" with the device itself.

With the goal of achieving safe HCI, *ad hoc* communication strategies may be fundamental. In [93], a user-centered design approach was used to create a guide for designers and developers of electronic communicable disease reporting systems. Such a goal was achieved by an ethnographic study based on semi-structured interviews and a focus group. The study reported in [94] pertained to practices and preferences for accessing health information by both medical staff and patients. The authors concluded that the Internet is the preferred channel to access the information, by also assessing its quality. However, miscommunication is critical. The work in [95] addressed the misinformation about unverified "cures" of cancer that can be found in tweets on the Twitter social network (Twitter Inc., San Francisco, CA, USA). Interestingly, the study suggested that users propagating the fake cures used a sophisticated language: they have knowledge about the medical domain but are not patients affected by this illness. Generally, user-centered design might be highly beneficial in different scenarios. Johnson *et al.* in [96] presented an extensive study on the formulation of a framework for guiding the redesign process for those systems which have been abandoned due to the lack of user-centered design. Accordingly, in [80], the end-users created their own tool to compensate for the inadequacy of health information technology. More specifically, the methodology design of a computer-based tool oriented to the information transfer and care coordination was described. In particular, the paper focused on a tool called "the clipboard", which is directly designed by nurse coordinators. The authors of [97] presented an electronic questionnaire for patients affected by skin cancer. The patient had to fill out it on a tablet and it was then integrated into his/her EHR to be discussed with the physician. Afterwards, the patient and the physician can make corrections and also add further information to enhance the data quality. The study in [98] considered a homecare setting, by focusing on motion pattern monitoring for elderly adults with memory disorders. Involving nurses in the design of the technology and providing opportunities to trial the system in real practice appeared beneficial for facilitating the system adoption. The study relied upon a qualitative approach conducted in a homecare unit serving older adults living in independent residences. Multiple data were collected, including individual and group interviews, a questionnaire with open-ended questions, evaluation probes, and system log data. The collected qualitative material was analyzed by a stepwise-deductive inductive approach. Indeed, computer-based healthcare systems can be designed for patients and installed in their homes.

4.2. Usability and performance evaluation

Several usability evaluation techniques are available and can be exploited and adapted to medical decision-making. The authors of [99] described a very interesting usability study on a mobile health app, called WiseApp, tailored to support persons living with Human Immunodeficiency Virus (HIV) in maintaining strict adherence to their anti-retroviral therapy. Three usability evaluations were conducted: think-aloud with end-users, usability evaluation with experts, and cognitive walk-through again with the end-users. The results of the study was that usability analysis involving end-users triggered iterative updates in the design of the app. For an in-depth GUI evaluation, the influence of emotions must be also considered. The authors of [100] considered the communication during tele-mental health psychotherapy sessions between a physician and a patient. In particular, this study showed that the emotions are involved in the decisional process, even when the physician-patient relationship is mediated *via* a computer, suggesting that emotional awareness is a key cognitive factor in remote diagnosis and therapy.

Regarding performance evaluation, Brown *et al.* in [101] presented the GUI design of an electronic audit and feedback system. These systems measure health professionals' performance and, in particular, the Performance Improvement plaN GeneratoR (PINGR) system was developed. It was composed of four modules: (*i*) clinical performance summaries, (*ii*) patient lists, (*iii*) detailed patient-level information, and (*iv*) suggested actions. The usability of this system was evaluated by eye-tracking, on-screen behavior, and questionnaires administrated to seven primary care physician recruited for the experimentation. Interestingly, the use of an eye-tracker device can estimate the uncertainty in decision-making during visual inspection of an image by analysis of oculomotor measurements (e.g., eye blinks and pupil diameter) [102]. More specifically, a group of 40 pathologists were examined with this technique while they were analyzing histological images of breast cancer [103]. The goal of the study was to evaluate the influence of pathologists' diagnosis by fixed case-level factors, their prior clinical experience, and their patterns of visual inspection. The study made use of 24 whole slide images related to four different types of cancer lesions, including benign ones. Both the pathologist's eye movement and the viewer tool behavior in terms of zooming and panning were analyzed. The results demonstrated the existence of complex interactions between the pathologist and the hypotheses that guide diagnostic decision-making.

Finally, computational methods and models can be defined for formal usability evaluation. In [104], a cascaded query model was proposed to resolve internal time-event dependencies in the queries that can have up to five levels of criteria; the procedure starts with a query for defining subjects to be recruited for a study, followed by a query to define the time span of the experiment, and then control group, control variables, and output variables. The model was implemented as an extension of the Clinical Data Analytics Language (CliniDAL) that is a restricted natural language previously proposed by the authors [105] as a query language for medical information systems. Usability evaluation of the overall framework was reported for three different scenarios. Florence *et al.* in [106] proposed a Patient-Oriented Prescription Programming Language (POP-PL). More specifically, the authors implemented a prototype of the language and evaluated its design by writing prescriptions in the new language, as well as administering a usability survey to medical professionals. Results of the usability study suggested that medical professionals can understand and correctly modify programs in POP-PL, and also provide insights for refining the language itself.

4.3. Usability in EHRs and CDSSs

EHRs and CDSSs must match specific usability criteria. The Task, User, Representation, and Function (TURF) framework for EHR usability was presented in [107]. Basically, these four components can determine the usability of an EHR system; all the components were described theoretically, and many examples of actual usability metrics in several case studies were provided. The authors stressed the idea that usability of EHR systems can be defined scientifically, as well as measured objectively and systematically. Rose *et al.* in [108] performed two separate usability studies, aiming at identifying the user workflows *via* a Web-based EHR. Unfortunately, issues regarding information visualization on the GUI, availability of visual cues and feedback emerged from these studies, affecting the primary care physicians' workflow. Regarding the EHRs in different countries, in [109], the authors proposed a study to investigate the usability level of Chinese hospital EHRs by assessing the completion times of EHRs for seven "Meaningful Use" (MU) relevant tasks conducted at two Chinese tertiary hospitals. A final comparison with relevant research studies conducted in United States EHRs was also presented. The total EHR task completion time for the investigated MU relevant test tasks showed no significant difference between the two Chinese EHRs and their American counterparts. Regarding EHR-powered applications in EDs, tools with iconic GUIs significantly outperformed (using Student's t-tests) the non-iconic version considering the Nielsen's heuristic evaluation, effectiveness, and user satisfaction [86]. A very interesting usability study was conducted by the authors of [110] where the clinicians interaction with electronic whiteboards were analysed using a “naturalistic” approach. Live videos of the users while interacting with electronic whiteboards were collected, along with screen captures of the whiteboards themselves, to record actual system interaction. All the materials were analyzed for usability purposes, and the results exhibited both immutable (that is system-related) and mutable (that is user-related) usability issues, which change as long as clinicians gain more experience in the use of the whiteboards. Whereas the focus is on the methodology, the paper provided several insights into the design of these medical devices. Along with diagnostic tasks, there are medical devices pertaining to the therapy side. For instance, infusion pumps are present in the hospital wards and are often used by nurses, especially in the ICUs, and several problems have been investigated in the literature. In [111], the Distributed Cognition for Teamwork (DiCoT) methodology was applied to evaluate how nurses use infusion pumps in an ICU. More recently, a heuristic usability study among four different infusion pumps was performed in [112]. Such a study still reveals issues in system status visibility, information access, and error prevention.

Aiming at overcoming the barriers for realizing the potential of CDSS adoption, usability testing, such as the think-aloud and near-live techniques, can be useful. In [113], a qualitative observational study was conducted on 12 primary care providers, by evaluating two CDSSs to estimate the risk of either pharyngitis or pneumonia among the patients. Both techniques revealed to be useful and complementary: the feedback during Think-aloud testing primarily helped to improve the tools’ ease of use, while the additional feedback from near-live testing was helpful for eliciting key barriers and facilitators to improve the current workflow. In [114], four user-centered design practices for the CDSS design were evaluated: pilot testing, provider satisfaction assessment, formal usability assessment, and analysis of the impact on performance improvement. The data were collected from 170 Veterans Affair primary care clinics; the practice of analyzing the impact of CDSSs on performance metrics seems to be the most effective. In this regard, the authors of [115] reviewed reports regarding EHRs and CDSSs and they deduced a list of good practises to design this kind of systems.

5. Clinical Decision Support Systems

Owing to the ever-increasing amount of biomedical data, which may lead to cognitive overload for physicians [61], CDSSs play a vital role to extract relevant knowledge about patient's health and well-being [61, 116]. Various aspects concerning the applications and the adoption CDSSs are described in the following sections.

5.1. Text Mining for optimized decision-making

Supporting health-related decisions and actions with pertinent and systematically organized clinical knowledge can improve healthcare service delivery [117]. The authors of [118] presented a CDSS, called ALgorithms for the MANagement of Acute CHildhood illnesses (ALMANACH), which informs the physician when a rapid diagnostic test to a child is required. In addition, ALMANACH advices about the treatment dosage and synchronizes the real-time data with a Health Management Information System for epidemiological assessment and decision-making. A classic prescription CDSS, named SafeRx®, reduced prescription errors even though its actual performance is decreased by high alert rates. The objective of the study conducted in [119] was to compare acceptance rates of alerts generated by SafeRx® and discover which factors allow for the alert acceptance and overriding. The authors of [120] developed a CDSS to avoid over-ordering of pre-operative investigations. The goal of such a system consisted also in reducing practice variance and improve adherence to well-established institutional pre-operative investigation guidelines. This CDSS can assist the physicians in decision-making, by integrating clinical protocols and information regarding a specific patient. In [121], a semi-supervised NLP methodology was adopted to analyze the free-text narratives in the report with the aim of identifying patients with urgent radiological findings that require a rapid communication to their referring physicians. Similarly, Becker *et al.* in [83] exploited an NLP analysis for patient-specific guidelines. In [89], a TM approach was proposed to predict hospital admissions using early medical records from the ED. This method could be used to manage daily routines in EDs, such as capacity planning and resource allocation. The icuARM CDSS proposed in [33] was an effective solution for supporting ICU care providers according to real-time data. To summarize, these systems can selectively and properly present the information to the clinicians, allowing for context-aware case-based reasoning. Regarding effective visualization techniques, Mane *et al.* in [122] proposed VisualDecisionLinc, a prototype leveraging visual analytics to provide aggregate data views for supporting the evaluation of effectiveness and risk regarding several therapeutic options for different sub-populations of patients, ultimately aiming at personalized care.

5.2. Internet-based and shared decision-making

Physicians regularly rely upon Internet search engines for Good Clinical Practice (GCP) guidelines, as well as novel research protocols. Changes in the clinical practice are obtained also relying upon "high impact" clinical studies that can be retrieved from the PubMed repository. In [123], an ML approach to identify high impact clinical studies in PubMed was presented. Aiming at classifying recently published articles, only static features, mainly independent on the time course, were considered (e.g., journal impact factor, authors' number, study sample size). Considering the wide distribution of patient's Internet health information-seeking, the patient-physician relationship is highly influenced [124]. Indeed, these systems engage the patient in the diagnostic and therapeutic decision-making processes: this patient-care centered approach might realize a shared decision-making approach, along with informed consent. Personalized and up-to-date patient information management is valuable. PHRs might be a key element in this process. The HealthDesign project was a multi-year, multi-site initiative to effectively improve the design of PHRs by means of a user-centered approach, even though privacy issues must be always considered [79]. Including patients' preferences in a CDSS to accomplish a patient-care centered approach is fundamental to effectively realize shared decision-making. In [125, 126] the MobiGuide architecture—aimed to establish a ubiquitous, user-friendly, patient-centered mobile CDSS for patients and for their care providers—was described. Patients resulted empowered by the system because their health status was continuously monitored *via* mobile sensors and self-reporting of symptoms. When health conditions required clinical attention, medical team components were informed appropriately, while patients were notified in parallel. The evaluation had demonstrated system capability for supporting distributed decision-making during its use by patients and clinicians with some important monitoring targets: blood glucose levels, ketonuria, and blood pressure. In [127], another CDSS oriented to shared decision-making was proposed: PANDEX; it consisted in a distributed application assisting patients and care providers to reach an optimal decision by using decision-analytic methods. The PANDEX prototype focused on genetic pre-natal consultation by taking into account patient clinical data and preferences. Wang *et al.* in [85] addressed shared decision-making processes in anti-hyperglycemic medication strategy decisions for patients with type-2 diabetes mellitus. Along with guidelines-based knowledge, a multilabel classification model—using class-imbalanced EHR data and providing a recommended list of available anti-hyperglycemic medications—aimed at supporting shared decision-making conversations between physicians and patients. In [128], the Shared Care Platform (SCP) was developed to support the continuity of care for multimorbidity patients, involving several physicians with different specialties. Aiming at improving communication and coordination among health professionals towards a clinical consensus, the SCP combined the Clinical Wall, a social network component allowing the different health professionals to discuss and define shared decisions, and a CDSS. Considering predictive models for reliable performance in multi-institutional scenarios, the authors of [129] developed a Web service for individual prognosis prediction based on multi-center clinical data collaboration without patient-level data sharing (POPCORN). POPCORN, by dealing with patient privacy and generalizable performance, exploited a multivariate meta-analysis and a Bayesian framework to provide a CDSS adaptable to highly variable application environments. The model was validated using a joint, multi-center collaborative research network between China and the United States recruiting patients diagnosed with colorectal cancer.

5.3. Pathology-oriented CDSSs

As expected, no general purpose CDSS exists, since they are often tailored to specific pathologies or clinical scenarios. For instance, the cardiovascular simulator in [37], reproducing the patient's condition for therapy testing, served a CDSS for specialist training. The work in [130] focused on liver fibrosis diagnosis. Even though the Fuzzy Analytical Hierarchy Process (FAHP) and Adaptive Neuro-Fuzzy Inference System (ANFIS) methods showed to be effective in diagnosis formulation of mortal diseases, they are generally not used in CDSSs. Therefore, the authors developed a CDSS based on the comparison of these two techniques; the experiments conducted in this work drew the conclusion that both of them can be used to implement a CDSS. Leveraging advanced technologies, telemedicine may provide support to diagnosis and monitoring, by also proposing therapeutical options and variations. Therefore, a CDSS can be integrated into a continuous care delivery framework for homecare. In [131], a telehealth system was presented, aiming at providing health services to patient at home. Such a system performs the integration of extracted clinical measurement parameters with a CDSS. The acquired telehealth data were analyzed by a rule-based engine and statistical methods to identify anomalies. Chronic obstructive pulmonary disease and chronic heart failure were considered as case studies to illustrate the potential benefits of this integrative approach for the management of both acute and chronic diseases. Glycaemia data were automatically acquired by the glucose meter and the diet was changed according to the current metabolic conditions; besides, the variation in insulin administration was notified also to physicians. Such a CDSS strongly reduces the face-to-face visits, since the patient can be daily monitored by physicians. Horta *et al.* [81] developed a CDSS based on a predictive model for the co-management of surgical patients in the post-operative ward setting.

5.4. User acceptance of CDSSs

The adoption of CDSSs might be strongly limited by user acceptance. Thus, effective design and evaluation models must be defined [132], by focusing on user-centered design approaches to identify target user needs [115]. Guidelines to design GUIs for health service planning for osteoarthritis care can be found in [133]. As a matter of fact, guidelines for CDSS design are valuable, such as the PICARD clinical guideline-based support architecture proposed in [134]. The usability of an EHR is expressed by the quality of the data contained in it. This concept was highlighted in [82], previously described in Section 3, where the authors classified the mistakes due to scarse HCI design. Richardson *et al.* [113] conducted think-aloud and near-live usability testing on two clinical decision support tools. In [114], four user-centered design practices for the CDSS design were evaluated: pilot testing, provider satisfaction assessment, formal usability assessment, and analysis of impact on performance improvement. In [135], semantic analysis was used to identify the reasoning and decision processes used by physicians in clinical tasks through an approach based on propositional analysis. The authors of [136] addressed the issues related to the standard procedures for multiple sclerosis evaluation. Indeed, the Expanded Disability Status Scale (EDSS), which is commonly used disability measure, was affected by inter-rater variability. The developed CDSS, called Automatic EDSS (AEDSS), aimed at increasing the EDSS reliability by forcing the neurologist to follow precise reasoning steps. A validation experiment involving four Italian institutions showed that AEDSS reduces inter-rater variability, and in many cases, can correct neurologist errors. In [47], an application to support physicians in managing patient's genetic profiles was subjected to usability test with positive results, as mentioned before.

6. Conclusions

Computerized systems that effectively support decision-making tasks are crucial in critical real-world applications. With reference to the clinical domain, in the latest years physicians have to manage and combine a huge amount of high-quality data mostly collected from EHRs, laboratory tests, imaging, and medical devices [3, 12]. Thus, decision-making in precision medicine involves several members of the healthcare staff, including paramedical and medical personnel, because expertise from different disciplines is needed to determine a diagnosis and perform a therapy in Multi-Disciplinary Teams (MDTs) [137]. Technological innovation is certainly important, but the human aspect is even more valuable: with the shared decision-making, the patient is proactively involved in the decision-making process while technology has to present safely the relevant information to the stakeholders.

In this work, an overview of the current applications and trends of HCI in clinical decision-making tasks was presented. Relying upon a systematic literature review, we pointed out the main topics involved in this fundamental aspect of digital healthcare. In particular, the analyzed literature articles (from the principal publishers in the scientific literature) were subdivided into six themes, namely: Interfaces, Visualization, EHRs, Devices, Usability, and CDSSs. Interestingly, these items typically presented overlaps among the themes, revealing that HCI inter-connects multiple topics (as shown in the graph-based taxonomy scheme in Fig. 1). With the goal of focusing on HCI and its design aspects, the selection of the articles under consideration was further refined, thus resulting in four clusters that are depicted in Fig. 2.

To summarize, safe interaction is fundamental in clinical decision-making and must be effectively supported by GUIs allowing for task-specific and personalized functionalities (see Section 2). As observed in Section 3, EHRs can provide an organized and up-to-date information collection for precision medicine. EHR-based data analytics and integration pose new challenges for data visualization, such as interactive dashboards to facilitate critical and time-constrained decisions in highly dynamic clinical environments (e.g., EDs, ICUs). Indeed, the latest ML and AI techniques (including TM, NLP, and Computer Vision) can dramatically improve the clinical workflows, especially with regard to the analysis of overwhelming amounts of data and repetitive manual tasks. With regard to overall usability results, formal usability evaluation may complement heuristic evaluation and cognitive task analysis during the iterative user-centered design process (see Section 4). These studies could also be endorsed by recording tools—such as keystroke and mouse click/movement logging or eye-tracking—in clinical decision-making tasks. Relying upon systematized datasets from EHRs and real-time monitoring, CDSSs can incorporate advanced AI tools to optimize clinical decision-making and workflows (as explained in Section 5), by augmenting explainable models with symbolic methods and reasoning engines. These AI-enabled computational platforms and infrastructures, which also take into account Cognitive Informatics principles, can adequately support shared decision-making and patient empowerment. Ultimately, user-acceptance must be carefully investigated since new CDSSs imply changes in the daily clinical routine. Therefore, the end-users have to feel confident and comfortable while utilizing the newly introduced computerized systems.

This study shows that adequate support to physicians in decision-making to formulate a diagnosis or to assign a therapy should not consist in a fully automatic system that yields a response by replacing the physician's work, just like a "crystal sphere"; indeed, in some cases, this automated response might be wrong and could irredeemably affect the physician's decision [5, 7]. On the contrary, the actual support to the physician might provide useful tools to interactively support his/her work with the goal of effectively facilitating the reasoning and making all the data available in a well-organized manner [14, 16]. Real-time remote data streaming is another opportunity to follow health events about the patient with continuously up-to-date data [22]. Novel techniques for the cooperative work with intelligent visualization [17, 61, 138] represent a suitable means to put in communication doctors with different specializations facilitating the second opinion process.

In conclusion, our review shows that advances in AI can effectively support the physicians' cognitive processes, which certainly play a central role in decision-making tasks. Indeed, AI tools cannot completely emulate and capture the human mental behavior: with respect to advanced ML techniques, the human mind might solve a complex problem even without a statistically significant amount of data by relying upon domain knowledge. Our study shows that the synergy between AI and HCI is fundamental for accurate and safe decision-making. With the goal of optimizing clinical workflows, CDSSs focus on interactive solutions for effectively supporting the physicians in their daily activities, by leveraging their unique knowledge and evidence-based reasoning, as well as improving the various aspects highlighted in this work.

Acknowledgement

This work was partially supported by The Mark Foundation for Cancer Research and Cancer Research UK Cambridge Centre [C9685/A25177].

Additional support has been provided by the National Institute of Health Research (NIHR) Cambridge Biomedical Research Centre. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health and Social Care.

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