Clinical Decision Support Systems in Practice: Current Status and Challenges

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***Abstract* - Decision support systems (DSS) are computer programs based on artificial intelligence methods that contribute to reaching a correct decision in an often-narrow domain of interest. Clinical decision support systems (CDSS) are such DSSs that may be used by medical professionals in clinics and hospitals. They are used for diagnosis, treatment protocol recommendations, treatment outcome predictions and other tasks. CDSS are constructed based on symbolic and machine learning (including deep learning) approaches to represent and infer medical knowledge. The aim of this work is to provide an overview of past and current methods in designing a successful CDSS. The study considers the systems that were claimed to be implemented in clinical practice. Currently, the development of a CDSS is mostly pursued in two directions: 1) a more traditional approach based on rules, ontologies, probabilistic models, and the use of standards; 2) machine learning based approach. Both approaches may be used complementary within a healthcare information system. This work seeks to provide an objective view on the advantages and limitations of the approaches as well to discuss future research avenues that could lead to more accurate and trustworthy CDSS and improved healthcare.**

Keywords - decision support system, clinical decision support system, healthcare, artificial intelligence, deep learning

I. Introduction

Artificial intelligence (AI) is used nowadays in a variety of application domains, with varying levels of success. Its application in healthcare is of paramount importance for transforming and improving the traditional medical workflows. The improvement needs to be made in a sense that it would benefit all the stakeholders (i.e. patients, medical personnel, clinic) in the process. The application of AI in medicine may be performed in different ways. According to [1], virtual and physical branches of AI may be distinguished. The virtual branch includes any informatics approaches, ranging from electronic health records (EHR), deep learning (DL), control of health management systems, and active guidance of physicians in their treatment decisions. The physical branch is best represented by robots and other hardware systems used to assist patients or a surgeon in a surgery room.

Clinical decision support system (CDSS) is a well-known name that refers to the program (virtual AI) that implements one or more AI methods into clinical practice in order to enhance medical decisions. Medical personnel may use CDSS for diagnosis, prevention, treatment protocol recommendations, care-coordination, treatment outcome predictions, and other tasks [2]. While there has been much progress reported in the efficiency of the artificial intelligence algorithms on various medical problems [3,4], still, the integration of AI solutions in a CDSS that performs well in clinical practice is rare and has proven to be notoriously difficult [5].

The development of CDSSs has been proceeding gradually, following the course of the improvements in AI algorithms, knowledge representation methods, software architectures and clinical data availability. While there are many AI approaches one could use for developing a CDSS, most of them can be classified into one of two classes: symbolic and machine learning (ML, including DL).

In this work, we consider the research approaches that were reported to be implemented in clinical practice or that were tested in real-clinical settings. We also briefly elucidate the principles of the underlying AI methods that were used in these systems. Since there has been many research works covering different aspects of CDSS in recent years, we stipulate the aim of this study as twofold: 1) a critical synthesis of current literature regarding the possibilities and challenges in implementing a successful CDSS, and 2) an overview of the best CDSS practices and challenges that, when overcome, have the potential to significantly improve healthcare.

Our work is structured as follows. In section II, we provide a critical review of the related work, with a focus on more general review studies that are related to CDSS. In section III, we provide an overview of the successful examples of CDSSs in practice. Then, in section IV, we delve into the AI technologies that underpin contemporary CDSSs. Section V is devoted to open challenges in designing and implementing a CDSS. We discuss some of the debatable CDSS topics in section VI. Finally, section VII concludes the paper.

II. Related Work

The topic of our paper resembles several studies in recent years that pursue the goal of systematization of knowledge about CDSSs or AI methods in healthcare and raise awareness about the challenges related to these topics. In continuation, we provide a brief critical assessment of several recent important scientific review papers that deal with CDSSs.

Castaneda et al. [6] provided a general review paper on CDSS in 2015. They stipulated the important role of EHR in employing CDSS, however they also pointed out that EHR adoption is only the first step towards improving patient healthcare, since its use may not lead to improved clinical outcomes if it is not supported by models constructed on large datasets, possibly derived from multiple databases. They consider that, currently, the use of CDSS in practice is limited, since they are mostly used to generate alerts, reminders and summaries. As a marked example of large-scale AI integrated CDSS, they mention IBM Watson, but also question its ability to improve treatment outcomes. The study also offers a valuable input on several real-world CDSS implementations.

The study of Middleton et al. [2] from 2016 offers a holistic 25-year retrospective and a 25-year vision in CDSSs. The study is an important source of information on evolvement of CDSSs in the USA, which includes mentioning of multiple CDSS implementations, some of which were used successfully in clinical practice. It describes six axes in CDSS development: data, knowledge, inference, architecture and technology, implementation and integration, and users, and provides elaboration along these axes. Several topics that adversely affect CDSSs are also discussed.

A review study by Dwyer et al. [7] from 2018 concerns the use of machine learning approaches in governing decisions in the field of clinical psychology and psychiatry. The review provides an insight into the potential for ML methods to augment clinical practice (diagnosis, prognosis and treatment) in the field, with description of the principles of these methods. The authors admit that there are very few successful CDSS implementations available and point to several reasons why this is the case, such as: cultural norms in clinical practice, validity of diagnostic and prognostic labels, representativeness of training data, mechanistic understanding of detected patterns, practical implementation, and others. Although CDSS implementations are not covered, the study is a relevant resource for understanding the AI algorithms that can be used in clinical psychology and psychiatry.

Topol [8] presented a recent review study dealing with the topic of high-performance medicine, in which he highlights the recent advances in AI, especially in DL and the applications in various medical domains. The author shares his opinion that the clinical practice is only at the starting point of using advanced DL approaches. The study is highly valuable as a harbinger of DL applications in CDSS, as it describes numerous important implementations, both of peer-reviewed publications of AI algorithms in healthcare and of FDA approvals of AI algorithms implementations. The study acknowledges the pitfalls of clinical implementations, with the example of IBM Watson, which in recent years made several erroneous recommendations that could have threatened patient safety. The author considers the current lack of prospective studies as a downside of DL-based CDSSs.

The study of Picardi et al. [9] deals with the significant topic of assurance in CDSSs. Especially, ML-based black-box models suffer from the issue of weak interpretation capabilities and generally low validity when the whole process is not closely controlled. The authors induce an assurance case pattern based on an important case study of retinal disease diagnosis. They suggest that the assurance pattern for a model should describe: a clinical setting (context of use), a benchmark (against a gold clinical standard), an ML model choices explanation, training and validation data sufficient to describe the clinical setting, an independent test data, and a thorough ML process explanation.

Kelly et al. [5] focus on key challenges for delivering clinical impact with artificial intelligence. Their study points to numerous existing challenges, including the ones that are inherent to ML methods, implementation and logistical difficulties, as well as the existing sociocultural barriers of adoption. They conclude that, based on the available reports, AI metrics such as accuracy, area-under-curve, and others often do not reflect clinical applicability, and especially any beneficial change in patient care. On that topic, they consider that clinicians need to be able to understand how the AI algorithms work, to improve patient care within a workflow they are familiar with, which is a topic often neglected in scientific papers. Regarding AI algorithms interpretability, they report that the recent European Union's General Data Protection Regulation (GDPR) legislation mandates the right to explanation for algorithmically generated user-level predictions that have the potential to significantly affect users [10].

The review study by Wang and Preininger [11] considers the state-of-the-art, challenges and future directions of AI applications in healthcare. They categorized the studies published in the period 2014 – 2019 into five separate categories according to the data type analyzed. These include multi-omics (genomics, proteomics, transcriptomics, etc.), clinical, behavioral, environmental, and pharmaceutical research and development data. They described each data type category, associated challenges and practical implications that have emerged over the last years. They stress out that both AI models' and data challenges exist that currently hamper the success of developed CDSSs.

Shu et al. [12] present the applications of AI methods in the field of pediatrics. The paper is valuable because of the multiple descriptions of AI research papers covering several medical branches in pediatrics (e.g. cardiology, neurology, radiology), as well as for a discussion on multi-omics research in CDSSs, including the consideration of cloud, clusters, and grid computing for high-precision medicine. Nevertheless, the work does not cover many successful practical implementations of CDSS, but instead focuses more on future perspectives and limitations that need to be overcome.

Krittanawong et al. [13] offer a practical view on DL-based AI methods applied to cardiology. They focus on explaining the properties, benefits and downsides of using these methods, and provide a guide to implementation options (e.g. hardware considerations, software packages, modeling strategies). Their work suggests that the use of DL in cardiology is still of limited extent in the number of conducted studies and that the studies may suffer from a positive publication bias, which remains to be discovered by future meta-analysis studies. Their work does not report on real-world CDSS implementations of DL.

III. An Overview of Successful Implementations of Clinical Decision Support Systems

According to Wright and Sittig [14], the evolution of CDSS architectures may be divided into four phases:

- Phase 1: Standalone decision support system
- Phase 2: Decision support integrated into clinical systems
- Phase 3: Standards developed for sharing content between clinical decision support systems
- Phase 4: Web service models for decision support systems

We consider that, from the AI perspective, a fifth phase, as a continuation of the fourth phase, may be distinguished, which includes big biomedical data analytics from the cloud and grid platforms using ML or DL approaches. The timeline presented in Fig. 1 illustrates some of the significant CDSSs either implemented in real-time clinical practice or demonstrated to be able to work in such a setting. The references for the shown CDSSs may be found in the studies [2,8,11,15–19]. The years listed in the figure are those of published research.

From Fig. 1, it can be observed that there is currently an abundance of high-quality research into ML and DL-based approaches, covering a great diversity of medical issues. It should be mentioned that only some of the most significant recent CDSS research works and implementations are depicted in Fig. 1, while there exist many others, especially those that use ML or DL methods in clinical settings.

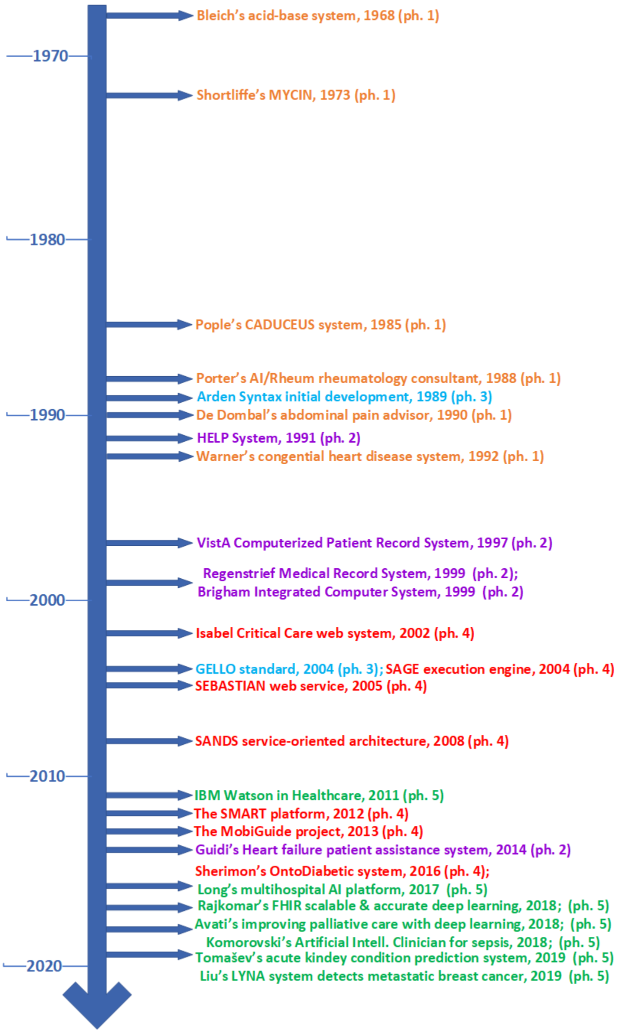

Figure 1. Significant CDSSs implemented in clinical settings or proven to work with real-time clinical data. Orange / violet / turquoise / red / green entries are for phase 1 / phase 2 / phase 3 / phase 4 / phase 5, respectively.

Aside from the clinical implementations of various CDSSs, in the last several years (i.e., from 2014), there has been a number of US Food and Drugs Administration's (FDA) approvals of proprietary AI algorithms and the accompanying platforms in healthcare (especially since FDA issued a fast-track approval plan for the AI algorithms in 2018). Some of these algorithms may be used for personal health assessment (e.g., via smart wearable devices), in primary care, or in clinical settings. Although a full list is not openly available, according to several resources, there are currently more than 50 such AI algorithms available [8,20].

IV. Clinical Decision Support System Technologies

A typical CDSS consists of a user interface (also called shell), an inference engine (also called core) and a data repository. As we have shown in the previous section, all CDSS components may be deployed in different settings, depending on the system architecture. The core usually implements one or more of the knowledge representation and reasoning schemes: symbolic and/or ML (also DL).

The symbolic (or declarative) approach includes all methodologies that deal with the representation of knowledge as a collection of symbols, including the relations among symbols. Such methodologies include formal mathematical logic (e.g., propositional, predicate, temporal), rule-based expert systems (they are an efficient subset of logic-based systems), imperfect knowledge inference systems (e.g. fuzzy rule-based systems, certainty factors, etc.), and Bayesian (probabilistic, belief) reasoning systems (e.g., Bayesian networks). The symbolic approach also includes biomedical computer ontologies, as a specific subtype of formal mathematical logic knowledge representation scheme (as ontologies are mostly based on description logic) [21].

The most common types of symbolic methods used in CDSSs are rule-based systems, ontologies and Bayesian networks [2,6]. A rule-based system usually contains an external (as a part of data repository) set of IF-THEN rules and valid facts. The reasoning may be performed either by forward or backward chaining. In forward chaining, the core makes the inference by matching the IF side of the rules with facts, resolves the conflict set (when more than one rule has its IF side satisfied), and activates (triggers, fires) the one selected rule, after which the reasoning cycle is repeated. Some of the advantages of using rule-based systems include:

- direct natural representation and the use of empirical knowledge acquired from an expert in a specific (narrow) domain
- modularity of knowledge collection and its simple maintenance
- efficient execution in narrow domains

- high interpretability of the automatic reasoning process

On the other hand, there are also some significant disadvantages of using rule-based systems:

- the rules acquired from the experts are heuristic and fragmentary ("knowledge nuggets") and do not explain the holistic relations in the process
- sometimes the rules may be contradictory, which is why maintaining consistency in a rule set is important
- the rules in a classical rule-based system are not robust and do not include uncertain and incomplete knowledge (this may be mitigated by using imperfect knowledge-based systems such as fuzzy rules)
- rule-based system stops being useful at the edge of the domain, while instead, like an expert, it should become monotonically weaker at problem solving
- clarifications, which result from the representation of chaining, do not provide causal connections in the process (there is no connection of ground or root causes with effects)

Unlike rule-based systems, ontologies are not intended primarily for executing actionable decisions. Instead, they are used as a mean to store hierarchical classification of terms and important relations among terms pertaining to a biomedical domain. They can be visualized as rather complex (meta)thesauri, covering different aspects of a biomedical topic or a more general biomedical knowledge domain. Contemporary ontologies use the open world assumption (which contrasts some important earlier knowledge organization schemes such as Frames [22]), under which no negation of a term's existence may be inferred unless its non-existence is explicitly stated. This somewhat limits their potential for constructing actionable rules [23]. Ontologies are mostly well-developed in the fields of biology and bioinformatics; however, they are still not well-integrated with other resources in implemented CDSSs [6]. Some of the reasons for this include:

- the complexity of biomedical vocabulary which limits the development of large ontologies
- integration of different ontologies is difficult
- slowness of the reasoning process for large ontologies

An example study by Gordon and Weng [24] used a semi-automated method to acquire data from diverse knowledge sources in order to evaluate and improve bacterial clinical infectious diseases ontology.

Bayesian networks may help medical experts in reaching accurate decisions [25]. They are based on probabilistic relations among nodes that represent variables that cover a topic. Both the structure of the network (the dependencies among variables) and the probabilities (either the a priori or the conditional ones) required by a network need to be derived from an expert's knowledge of a problem or from a dataset that representatively describes the covered topic. This, as well as the issue of interpretability of the reached decisions, severely limits their usefulness in CDSSs.

Machine learning techniques may be used in order to reach decisions based on available domain data. They cover a range of options, depending on the goal of the medical analysis: classification, regression, clustering, semi-supervised learning, etc. [7]. A simple division of ML techniques may be given in two categories: 1) black-box techniques, and 2) techniques that provide comprehensible models. Black-box ML techniques include support vector machines, artificial neural networks, ensembles of models (e.g. random forests) and other, nonlinear function-based models. Comprehensible models include linear and logistic regression models, decision trees and induction rules.

Deep learning can be considered as a specific subtype of machine learning that includes artificial neural network architectures consisting of multiple hidden layers with various transfer functions. Generally, DL methods are good at obtaining low-level feature representations from raw data, which enables them to be used out-of-the-box, i.e. without the significant human effort put into the engineering of higher-level features [11]. On the downside, all DL architectures may be considered as black-box models, since the distribution of weights in a network does not allow for an easy way of understanding why a decision is reached. The most common types of DL architectures used in CDSSs in the biomedical domain include:

- Convolutional neural networks (CNN) – by far the most common architecture type for biomedical imaging applications [8], consisting of multiple hidden convolutional and pooling layers
- Recurrent neural networks (RNN) – used most often for physiological time series modeling such as in cardiology or neurology, but also in predicting events onset [26]. Here, several subtypes of RNNs are used often, such as long-short term memory (LSTM) networks [27] and gated recurrent unit (GRU) networks [26]
- Deep belief networks (stacked restricted Boltzmann machines) [28, 29]
- Autoencoders – for unsupervised learning tasks, including dimensionality reduction and representation learning [29]

V. Clinical Decision Support Systems Open Challenges

The successful use of CDSSs in practice still suffers from some challenges that need to be properly addressed. In Table I, we compile a list of some frequently mentioned challenges discussed in the literature, which we categorize into major and minor ones, depending on our consideration about their relevance and the ability to be overcome. In continuation, we reflect on the major challenges.

AI model transparency (comprehensiveness) should be sought where possible in CDSSs. Due to the black-box nature of most ML and DL models, human needs to be present when reaching the final decision [11]. Additionally, providing a model interpretation is needed in healthcare, which is also enforced by GDPR [5].

Clinical workflows lack standardization for insertion points that can be used by developed CDSSs [2]. While

TABLE I. OPEN CHALLENGES FOR CLINICAL DECISION SUPPORT SYSTEMS

Challenge type	Short description	Reference
Major	AI model transparency	[5, 7, 11, 13]
Major	Standardization of DCSS integration into clinical workflow	[2, 7, 11]
Major	AI algorithms effectiveness	[5, 11, 13]
Major	Standardization of EHR data	[11, 30]
Major	EHR data are heterogeneous, sparse and noisy which hinders analysis	[11]
Major	Efficient external validation	[5, 7]
Major	Data integration from multiple sources	[5]
Major	Secure and scalable sharing of clinical data	[31]
Major	Data representativeness is lacking	[7, 11, 13]
Major	Regulation and rigorous quality control of AI devices is needed	[5]
Minor	Currently, too few prospective studies	[5]
Minor	Increasing trend of proprietary algorithms development	[11]
Minor	Positive publication bias in medical studies of ML and DL	[13]
Minor	Adversarial attacks as security risk	[5, 11]
Minor	Computationally expensive analysis of physiological data	[11]
Minor	Integrative analysis of physiological with other clinical data is lacking	[11]
Minor	Rapid development of new technology – many legacy systems	[2]
Minor	Behavioral data are heterogeneous, difficult to obtain ground truths	[11]
Minor	Environmental data linking with EHR data is needed for precision medicine	[11]
Minor	Heterogeneity of multi-omics data impedes its analysis and integration	[11]
Minor	Large scale knowledge engineering and management	[2]
Minor	Better understanding of human-computer interaction	[5]
Minor	Implementation issues: algorithms unavailable, too much training needed, not commercially viable	[7]
Minor	Data quality and diversity needs to be considered in addition to quantity when assessing ML and DL methods	[13]
Minor	Replication of study should be possible – models, data and code should be made openly available	[13]
Minor	Reporting of model results should be more elaborate with respect to metrics used	[13]

current practice inserts a CDSS where needed in the physician's workflow [11], the clinical practice would greatly benefit from having a more theoretically well-founded integration procedure.

Peer-reviewed randomized control trials need to be pursued where possible, since current practice shows that higher-accuracy AI systems do not necessarily result in better patient outcomes due to clinical inapplicability. Several researchers point to the necessity of improving patient outcomes as the ultimate goal of using CDSSs [5,13] Also, state-of-the-art performance of AI algorithms in many health applications is far from perfect, which leads to the question of the advanced AI algorithms effectiveness in practice. Currently, in some cases, results for DL vs simple logistic regression may not be favorable for DL [11]. It should be noted that due to the overfitting problem, sometimes simpler methods are more efficient and more practical [13]. Some of the unfavorable results may stem from too few dedicated DL model architectures specifically designed for medical images, which is mostly due to too few shared medical datasets. In these cases, transfer learning from natural images is used, which may be suboptimal [11].

Logistical problems that are related to data integration for efficient model construction abound. Namely, most of the healthcare data is not prepared for ML, as there are many image archival systems, EHRs, electronic prescribing tools and insurance databases available [5]. In this respect, unified data formats such as FHIR [30] could be beneficial; however, EHR data is still heterogeneous and has inconsistent semantic coding, which prevents data preparation for ML [11].

For efficient external validation of the model used by CDSS, site-specific adaptations need to be considered for generalizations (external dataset curation). A problematic fact reported is that very few (only about 6%) of medical studies perform external validation on datasets from outside of current institution [5]. The data representativeness is the problem of not having appropriate samples to construct a widely applicable model (e.g., there were too many light-skinned and too few dark-skinned images available for skin lesions classification [11]). One of the solutions to this problem is to increase the dataset size to include all the needed sample variations in a significant amount.

Scalable sharing of clinical data is a major challenge for the fifth CDSS architecture phase, since the abundance of medical data prevents previous solutions for data storage and sharing. In order to handle this challenge, cloud-based solutions seem to be a viable option, but this must be pursued on the scale of multiple hospitals in order to ensure CDSS validity. Secure and scalable information sharing may use blockchain or similar technology [31].

VI. DISCUSSION

It is a common assumption that a person working in a partnership with an information resource, such as a CDSS, is better than the same person unassisted [2,5]. However, a physician should take care when interpreting the results of CDSS recommendations. Any user, including the physician and the patient, needs to understand the CDSS benefits and limitations, and needs to be clear about which questions one can ask of the CDSS.

Currently, the development of AI methods by clinicians on-site instead of expertly designed models is still unsatisfactory due to the complexity of the AI methods in CDSS systems, but shows some advancements [32].

Explainable AI has seen a recent resurgence as a hot research topic in DL [11]; however, its results are still unsatisfactory for healthcare. We suggest that a viable option would be to use black-box or weakly understandable models only for image/signal analysis, and interpretable models for all other CDSS considerations (such as, for example, medical guidelines-based recommendations).

VII. CONCLUSION

This study has revealed that the successful implementations of CDSSs in practice are still uncommon and that there are many challenges that need to be overcome before CDSSs become ubiquitous. Since medical institutions have always strived to instill the highest level of trust in the patients that are admitted and treated there, the question of using AI-algorithms guided CDSS to improve patient outcomes is still debatable. Nevertheless, we consider that future, carefully conducted studies will show that the use of accurate and reliable CDSS is possible and that clinical practice would greatly benefit from its introduction into medical workflows.

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