Digital Health and Informatics Innovations for Sustainable Health Care Systems
J. Mantas et al. (Eds.)

doi:10.3233/SHTI240785

Integrated Perspectives on Clinical Decision Support: A Comparative Analysis of Knowledge Management Approaches

Moritz GROB[a,b], Robert A. JENDERS[c], Andrea RAPPELSBERGER[a], and Klaus-Peter ADLASSNIG[a,b,1]
[a]*Medical University of Vienna, Center for Medical Data Science, Institute of Artificial Intelligence, Spitalgasse 23, 1090 Vienna, Austria*
[b]*Medexter Healthcare, Borschkegasse 7/5, 1090 Vienna, Austria*
[c]*Charles Drew University & University of California, Los Angeles, CA, USA*
ORCiD ID: Moritz Grob 0009-0006-7867-9465, Robert Jenders 0000-0002-3389-6718, Andrea Rappelsberger 0009-0001-0345-4011, Klaus-Peter Adlassnig 0009-0008-5046-1549

Abstract. We analyze five approaches to knowledge management in clinical decision support (CDS) systems: pattern recognition based on annotated imaging data, mining of stored structured medical data, text mining of published texts, computable knowledge design, and general or specific text corpora for large language models. Each method's strengths and limitations in automating clinical knowledge management while striving for a zero-error policy are evaluated, offering insights into their roles in enhancing healthcare through intelligent decision support. The study aims to inform decisions in the development of effective, transparent CDS systems in clinical and patient care settings.

Keywords. clinical decision support systems, knowledge management, artificial intelligence, patient care

1. Introduction

Clinical decision support (CDS) systems leverage various forms of clinical knowledge to enhance patient care. These systems range from early approaches to computer-assisted diagnosis [1], machine learning (ML) [2], and medical expert systems [3] to more modern methods such as the design of computable biomedical knowledge [4], big data ML [5], and most recently large language models (LLMs) [6].

CDS—by definition and in its simplest expression—is the application of clinical knowledge to patients' medical data [4]. A core objective is to automate clinical knowledge management—acquisition, formalization, and maintenance of clinical knowledge—to the extent possible in order to optimize clinical decision-making while striving for a zero-error policy. Effective knowledge management ensures that clinical knowledge is systematically acquired, structured, and maintained, enabling reliable CDS systems.

[1] Corresponding Author: Klaus-Peter Adlassnig; E-mail: klaus-peter.adlassnig@meduniwien.ac.at.

2. Methods

Medical knowledge for CDS needs to be generated or acquired, technically administered, versioned, and regularly revised. Decision-makers, including patients' caregivers (physicians, nurses, infection personnel, and others), need to be made aware of the strengths, limitations, and weaknesses of the knowledge [7].

We describe five sources of medical knowledge, analyze strengths and weaknesses, and show how these different kinds of medical knowledge can be and are applied in CDS systems. Based on this analysis, we infer future trends and anticipate some success and failure.

3. Results

Five epistemologically distinct approaches to CDS and knowledge management shall be distinguished. They are depicted in Figure 1 and discussed throughout the following sections.

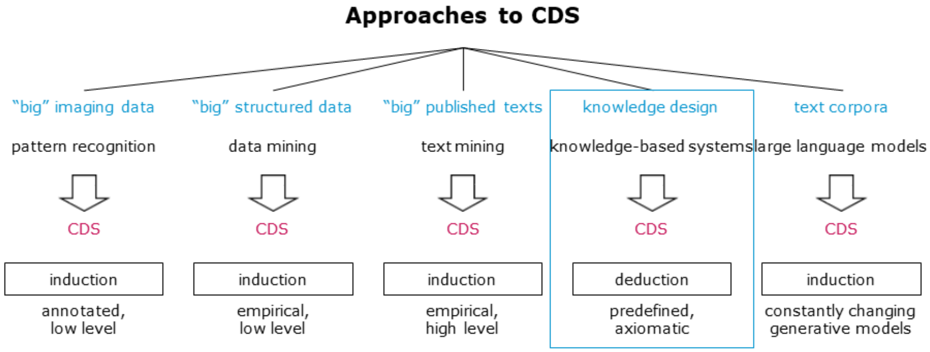

Figure 1. Overview of the five approaches to knowledge management for clinical decision support (CDS) discussed in this paper. We differentiate the approaches epistemologically: by their data source as well as their method of knowledge acquisition.

3.1. Pattern Recognition of Imaging Data

Image recognition arguably is currently the most widely used application of artificial intelligence (AI) in the form of ML in medicine, as 87% of AI/ML-enabled medical devices authorized by the United States Food and Drug Administration (FDA) in 2022 belonged to the category of radiology [8].

These applications use an inductive approach and have gained a lot of attention in recent years due to reports of expert-level results achieved by deep learning algorithms [9]. However, there remain doubts about the direct application to individual patient care due to its narrow clinical focus as well as missing model explainability [9]. Furthermore, a recent study has found an increase of false-positive findings due to commercially available ML tools in radiology [10], underscoring the need for further research in this area while a first randomized, controlled clinical trial has shown the potential viability of such tools [11].

3.2. Data Mining of Structured Data

Mining of uninterpreted medical raw data contained in an electronic health record (EHR) or similar system (e.g., patient history data, signs from physical examination, laboratory test results) within specific clinical contexts is a form of empirical, low level knowledge management. Since this data mining typically makes use of vast amounts of data to inductively infer knowledge, we use the term "big" raw data for this approach [5].

An example of use of this approach can be found in the United States National Institute of Health (NIH)'s Informatics for Integrating Biology and the Bedside (i2b2) framework [12] which is mostly used for cohort discovery in EHRs. Another example can be found in IBM's Watson which ultimately failed to gain a foothold in clinical practice as it was unable to generalize from patients' EHR data as accurately as hoped [13]. However, an approach to improve the viability of such a data mining approach in CDS systems using a closed loop "Learning Healthcare System Cycle" has been proposed by Dagliati et al. [12].

3.3. Text Mining of Published Texts

By text mining of published expert statements, consensus guidelines, and scientific state-of-the-art documents, higher levels of medical knowledge can be utilized than with uninterpreted medical raw data or mere abstracts of published texts [14].

This higher level, empirical, and inductive approach is sometimes combined with low level raw data mining to provide more in-depth CDS. An example is again IBM's Watson which failed to properly generalize knowledge from scientific literature in a similar way as from patient-oriented data [13]. Some of the technical limitations of this approach are discussed by Westergaard et al. and include the inconsistent use of a standardized format [14].

3.4. Computable-Knowledge Design

Computable clinical knowledge design contrasts the other presented approaches in its deductive usability once established. It deterministically applies axiomatic medical knowledge—accepted clinical knowledge that is predefined by domain experts and thus, once established, requires no further proof for the applied system—to structured medical raw data. The formalization of this knowledge enables logically provable inferences and the verification of a knowledge base's consistency [15], thereby supporting a zero-error policy in CDS systems.

This approach is the most prevalent of the discussed [4] despite being labor-intensive, requiring the manual formalization of clinical knowledge or guidelines in an executable format such as Arden Syntax [16] or the Clinical Quality Language (CQL) [17]. This formalization leads to increased explainability, reliability, and testability compared to inductive approaches, facilitating robust and transparent CDS.

3.5. Large Language Models

LLMs are deep neural networks trained on vast corpora of unlabeled texts with the ability to generate human-like responses to free-form input. Recently, they have attracted significant interest in the domain of clinical knowledge management due to their capability of interpreting and inductively synthesizing vast amounts of unstructured data, as a number of studies exploring the clinical utility of LLMs have been published or are currently in the process of publication [18].

Most currently available LLMs are designed for general-purpose use, thus their responses cannot be expected to meet the high standards needed in clinical practice. Approaches for alignment to the safety-critical medical domain, such as Google's Med-PaLM, have been proposed, but are unable to outperform clinicians as of yet [6]. Furthermore, standardized frameworks for evaluation are lacking [18].

4. Discussion

In clinical knowledge management—as in general—both inductive and deductive methods play crucial roles. Inductive approaches like ML draw on large datasets to identify patterns and associations in patient data. While this method can improve accuracy over time, it is important to note that these associations are not necessarily causal, which can lead to opaque or incorrect conclusions.

On the other hand, deductive methods apply structured, established knowledge to patient data. This approach uses a knowledge processing engine to match data against a set of digitized rules or definitions, offering explainability and transparency regarding limitations of the knowledge base. While sometimes challenging due to potential errors in data or unexplored clinical patterns, this method provides a clear, logical framework for decision making.

Currently, deductive knowledge design remains widely used in CDS systems. Although ML and other inductive tools are gaining attention, their practical adoption in clinical settings varies. For instance, image data pattern recognition has seen significant progress with FDA-approved medical devices and ongoing clinical trials. In contrast, data mining has failed to meet the high expectations placed in it for clinical usefulness while it is still used in medical research, e.g., for cohort discovery. LLMs have demonstrated enormous potential but are still in early development stages. Whether they will overcome the problems of proper generalization and fault tolerance ("hallucinations") to enable use in clinical practice remains to be seen.

As CDS evolves, a combination of inductive and deductive approaches is likely to prevail. Each method complements the other, with inductive methods helping to identify new associations and deductive methods applying these insights in a structured, deterministic context. The interplay of these approaches enhances the cycle of knowledge discovery and application, with ML playing a crucial role in accelerating this process.

5. Conclusions

CDS systems, as intelligent information technology (IT) implemented in healthcare, aim at enhancing service delivery by embracing best practices, optimizing outcomes, and ensuring the safety of both patients and healthcare workers. The integration of both inductive and deductive approaches offers a balanced strategy for decision-making, not only broadening the scope of CDS but also enabling greater accuracy and reliability.

However, the path to fully realize the potential of IT-augmented health services is not without challenges. Key barriers include gaps in content and process quality, the need for more structured data, standardization in data formats and terminologies, and of course adequate funding. Additionally, overcoming mental barriers—ranging from resistance due to a lack of understanding to skepticism about the potential for meaningful impact—is crucial.

References

[1] de Dombal FT. Computer-aided diagnosis and decision-making in the acute abdomen. J R Coll Physicians Lond. 1975;9(3):211–218.

[2] Baxt WG. Use of an Artificial Neural Network for the Diagnosis of Myocardial Infarction. Ann Intern Med. 1991;115(11):843–848. doi: 10.7326/0003-4819-115-11-843

[3] Shortliffe EH, Davis R, Axline SG, Buchanan BG, Green CC, Cohen SN. Computer-based consultations in clinical therapeutics: Explanation and rule acquisition capabilities of the MYCIN system. Comput Biomed Res. 1975;8(4):303–320. doi: 10.1016/0010-4809(75)90009-9

[4] Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ Digit Med. 2020;3:17. doi: 10.1038/s41746-020-0221-y

[5] Herland M, Khoshgoftaar TM, Wald R. A review of data mining using big data in health informatics. J Big Data. 2014;1:2. doi: 10.1186/2196-1115-1-2

[6] Singhal K, Azizi S, Tu T, Mahdavi SS, Wei J, Chung HW, et al. Large language models encode clinical knowledge. Nature. 2023;620(7972):172–180. doi: 10.1038/s41586-023-06291-2

[7] Hongsermeier T, Glaser J. Managing the investment in clinical decision support. In: Greenes RA, Del Fiol G, editors. Clinical Decision Support and Beyond. 3rd ed. Elsevier Academic Press; 2023. p. 603–626. doi: 10.1016/b978-0-323-91200-6.00021-8

[8] U.S. Food and Drug Administration. Artificial Intelligence and Machine Learning (AI/ML)-Enabled Medical Devices [Internet]. Silver Spring (MD): FDA; 2023 [cited 2024 March 27]. Available from: https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-aiml-enabled-medical-devices

[9] Kelly BS, Judge C, Bollard SM, Clifford SM, Healy GM, Aziz A, et al. Radiology artificial intelligence: a systematic review and evaluation of methods (RAISE). Eur Radiol. 2022;32(11):7998–8007. doi: 10.1007/s00330-022-08784-6

[10] Lind Plesner L, Müller FC, Brejnebøl MW, Laustrup LC, Rasmussen F, Nielsen OW, et al. Commercially Available Chest Radiograph AI Tools for Detecting Airspace Disease, Pneumothorax, and Pleural Effusion. Radiology. 2023;308(3):e231236. doi: 10.1148/radiol.231236

[11] Lång K, Josefsson V, Larsson AM, Larsson S, Högberg C, Sartor H, et al. Artificial intelligence-supported screen reading versus standard double reading in the Mammography Screening with Artificial Intelligence trial (MASAI): a clinical safety analysis of a randomised, controlled, non-inferiority, single-blinded, screening accuracy study. Lancet Oncol. 2023;24(8):936–944. doi: 10.1016/s1470-2045(23)00298-x

[12] Dagliati A, Tibollo V, Sacchi L, Malovini A, Limongelli I, Gabetta M, et al. Big Data as a Driver for Clinical Decision Support Systems: A Learning Health Systems Perspective. Front Digit Humanit. 2018;5:8. doi: 10.3389/fdigh.2018.00008

[13] Strickland E. IBM Watson, heal thyself: How IBM overpromised and underdelivered on AI health care. IEEE Spectr. 2019;56(4):24–31. doi: 10.1109/mspec.2019.8678513

[14] Westergaard D, Stærfeldt HH, Tønsberg C, Jensen LJ, Brunak S. A comprehensive and quantitative comparison of text-mining in 15 million full-text articles versus their corresponding abstracts. Rzhetsky A, editor. PLOS Comput Biol. 2018;14(2):e1005962. doi: 10.1371/journal.pcbi.1005962

[15] Moser W, Adlassnig KP. Consistency checking of binary categorical relationships in a medical knowledge base. Artif Intell Med. 1992;4(5):389–407. doi: 10.1016/0933-3657(92)90022-h

[16] Jenders RA, Adlassnig K-P, Fehre K, Haug P. Evolution of the Arden Syntax: Key Technical Issues from the Standards Development Organization Perspective. Artif Intell Med. 2018;92:10–14. doi: 10.1016/j.artmed.2016.08.001

[17] Jenders RA, Rhodes B. Decision rules and expressions. In: Greenes RA, Del Fiol G, editors. Clinical Decision Support and Beyond. 3rd ed. Elsevier Academic Press; 2023. p. 281–308. doi: 10.1016/b978-0-323-91200-6.00011-5

[18] Park YJ, Pillai A, Deng J, Guo E, Gupta M, Paget M, et al. Assessing the research landscape and clinical utility of large language models: a scoping review. BMC Med Inform Decis Mak. 2024;24:7. doi: 10.1186/s12911-024-02459-6