Challenges of Trustable AI and Added-Value on Health
B. Séroussi et al. (Eds.)
© 2022 European Federation for Medical Informatics (EFMI) and IOS Press.
This article is published online with Open Access by IOS Press and distributed under the terms of the Creative Commons Attribution Non-Commercial License 4.0 (CC BY-NC 4.0).
doi:10.3233/SHTI220505

Towards the Improvement of Clinical Guidelines Based on Real World Data

Elisa HENKE[a,1], Ines REINECKE[a], Michele ZOCH[a], Martin SEDLMAYR[a], and Franziska BATHELT[a]
[a] *Institute for Medical Informatics and Biometry, Carl Gustav Carus Faculty of Medicine, Technische Universität Dresden, Dresden, Germany*

Abstract. Computerized clinical guidelines (CCG) are effective instruments for standardizing, monitoring and optimizing medical treatment processes. Nevertheless, due to barriers in flexibility, transferability and acceptance, the widespread use of CCG in clinical practice is not yet common. To overcome those issues, we present a concept on how to use real world data to evaluate CCG and to recommend improvements. As a first result, we defined an algorithm to extract treatment processes based on the standardized Observational Medical Outcomes Partnership (OMOP) Common Data Model as well as their visualization using the graphical modeling language Business Process Model and Notation (BPMN).

Keywords. Business Process Model and Notation, OMOP CDM, computerized clinical guidelines, interoperability

1. Introduction

Computerized clinical guidelines (CCG) are effective instruments for standardizing, monitoring and significantly improving processes in healthcare [1][2]. Nevertheless, barriers exist that prevent the adaption in clinical practice. Studies agree the most relevant reasons for those issues are: the lack of flexibility, transferability, acceptance and trust, resulting from a lack of evidence based on real world data (RWD) [3][4][5]. To address these gaps, Jin et.al. suggest to compact information through visualizations and to link CCG with electronic health record (EHR)-data [5].

To support technical transferability and comparability it is beneficial to use a standardized common data model (CDM) including standardized vocabularies and terminologies that ensure semantic interoperability across countries and healthcare fields. The Observational Health Data Science and Informatics (OHDSI) [6] provides the Observational Medical Outcomes Partnership (OMOP) CDM that gained significant relevance in the last years for research on RWD [7]. For comprehensive process visualization Business Process Model and Notation (BPMN) is considered as valuable asset in the healthcare section [8]. In this paper, we present a concept based on OMOP CDM and BPMN on how to use RWD to evaluate CCG and to recommend

[1] Corresponding Author, Elisa Henke, Institute for Medical Informatics and Biometry, Carl Gustav Carus Faculty of Medicine, Technische Universität Dresden, Dresden, Germany; E-mail: Elisa.Henke@tu-dresden.de.

improvements. We show preliminary results addressing the extraction of treatment processes for single patients as BPMN models based on OMOP CDM data.

2. Methods

2.1 Concept

Our concept (Figure 1) is based on EHR data stored in the OMOP CDM, which implies a standardization of data and allows comparability independent from the location of the hospital. Leveraging the OHDSI software stack allows researchers to define and share cohort definitions among sites. A cohort definition groups different patients with similar characteristics such as the treatment process. This information stored on the OMOP CDM database level can be further analyzed regarding patterns, i.e. common parts in the treatment plans, that are promising for positive outcomes. With that, a common clinical treatment process could be synthesized. This common treatment process is evaluated based on retrospective data with positive and negative outcomes. If it is hereby indicated that the common treatment process may increase the possibility of positive outcomes, it can be utilized to evaluate an associated CCG by finding contradictions, differences or overlaps, which results in recommendation for CCG related improvements. If synthesis of a common process is not possible due to too many differences in local treatment plans, it may be possible to synthesize several common treatment plans and assesses their possibilities for positive outcomes against each other. If that is not possible either, the treatment plan elements can be prioritized.

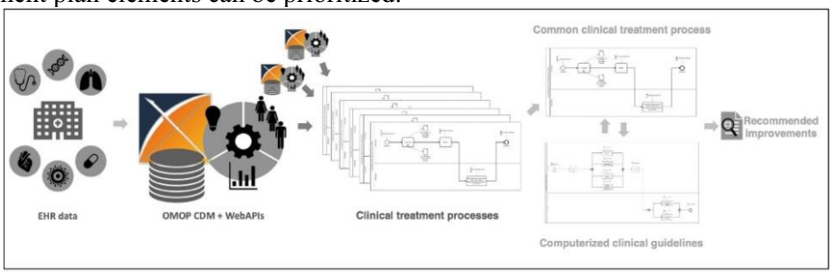

Figure 1: From EHR data to recommended CCG improvements – a concept (own illustration)

2.2 Requirements for Automatic Extraction of Treatment Processes from OMOP CDM

According to the data stored in OMOP CDM an algorithm to extract treatment processes as models in BPMN version 2.0 was defined [9]. In an interdisciplinary team, we have manually analyzed existing BPMN models of clinical treatment processes [10][11] and agreed on criteria for a BPMN model to be sufficient, when (a) for a single medical case, (b) treatment relevant parameters, (c) the chronological order of events, (d) parallel events and (e) involved actors are shown in the visualization.

2.3 Access the process relevant data within the OMOP CDM

Process relevant data elements required in OMOP CDM were identified based on the analysis of the guidelines for stroke treatments. These data elements are stored in

following tables within OMOP CDM v5.3.1. according to the implementation of Gruhl et.al [12]: VISIT_OCCURRENCE, MEASUREMENT, CONDITION_OCCURRENCE, PROCEDURE_OCCURRENCE, and VISIT_DETAIL, CARE_SITE and CONCEPT.

2.4 Automatically generate BPMN models

First, we designed an algorithm that maps the process relevant OMOP CDM data elements identified in section 2.3 to BPMN elements. Second, we implemented the algorithm in Java as a prototype and tested it with anonymized data based on the core data set of the Medical Informatics Initiative Germany [13]. For visualization purpose the automatically generated treatment processes were imported into the software Camunda Modeler (Version 4.0.0) [14] via its interface. Our implementation automatically generates a .bpmn file out of OMOP CDM data that meets the interface specification.

3. Results

3.1 Link relevant data to BPMN model element

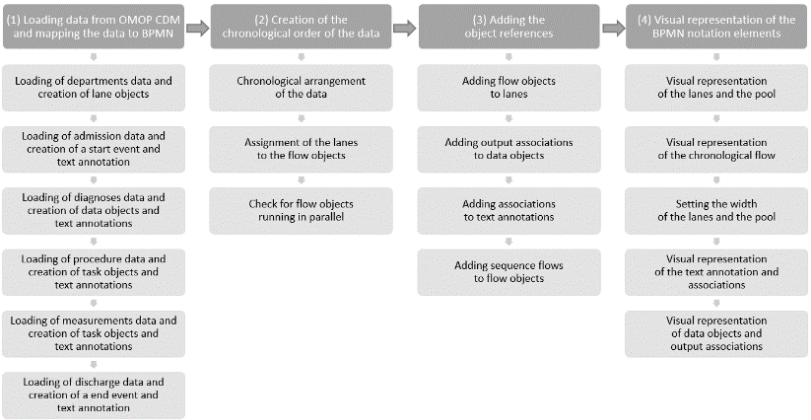

Figure 2: Algorithm to automatically model treatment processes with BPMN by extracting data from OMOP CDM (own illustration)

The necessary data elements (see section 2.3) are mapped to BPMN elements (Figure 2 – step 1). The complete mapping table is accessible through the supplemental files[2]. In step 2 data is put into a chronological order based on the comparison of timestamps and followed by the arrangement and assignment of the data to corresponding "*lanes*". As different events may have the same timestamps, the data is also checked for concurrency. If parallel events occur, two *"parallel gateways"* are used for branching and merging the process flow. In the third step object references are assigned, that specify which BPMN notation elements are connected to each other. Step 4 comprises the complete visual

[2] https://caruscloud.uniklinikum-dresden.de/index.php/s/8cNfm8kpwCdJ63e

representation of the whole treatment process including automatic layouting of the constructed elements.

3.2 Automatically generate BPMN models

The method defined in section 2.4 was applied on five medical cases of different patients. It resulted in BPMN models as roughly shown by example in Figure 3. The exact models can be found in the supplemental files[2]. Each resulting BPMN model has confirmed being correct according to original data by at least two persons.

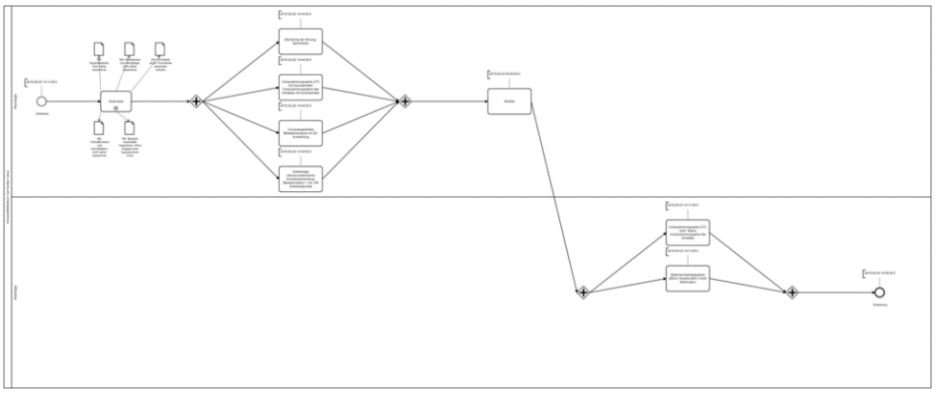

Figure 3: Automatically created BPMN model (own illustration; tool: Camunda Modeler)

4 Discussion & Conclusion

To the best of our knowledge, there is no approach that uses data stored in OMOP CDM to gain evidence for the accuracy of CCGs [7]. With the presented extraction, a first promising step to realize and evaluate the concept to improve CCGs based on RWD stored in OMOP CDM has been made. This enables us to automatically extract patient treatment processes from OMOP based data in more detail than existing approaches that are able to visualize a patient related clinical report including a summary (amount) of observations, procedures, diagnoses etc. [15], to find similarities in medical treatments like diabetes, hypertension and depressions [16] or for pediatric epilepsy [17]. The OHDSI applications ATLAS “Cohort Pathways” and “Profiles” [6], visualize a summary of medical treatments for specific conditions over a patient cohort as sunburst plot and support a visualization for events over a time period, representing clinical events within different domains (e.g. observations, measurements, etc.), respectively. However, a representation of the treatment process for a single visit including involved actors is not realizable with these approaches. Our approach can represent the treatment process as BPMN model and meets the initially stated criteria (section 2.2). With that, we addressed the strategies stated by Jin et.al. [5] namely information visualization and linkage to EHR data. Nonetheless, our approach is a prototype that has been evaluated only on five medical cases and is currently limited to a restricted set of parameters, due to the initial focus on the diagnosis stroke. Despite these required optimizations, we will work on the synthesis of an optimized treatment process from the set of treatment processes, which

comes with immense challenges and the comparison to specific guidelines. For both cases, we aim to evaluate the options delivered by BPMN and the comparison of different models [18].

Declaration

Conflict of Interest: The authors declare that there is no conflict of interest.

Author contributions: EH and FB: conception of the work. FB defined the concept, while EH designed and implemented the OMOP CDM to BPMN algorithm. All authors contributed substantial ideas and participated in editing and revising of the manuscript. All authors approved the manuscript in the submitted version and take responsibility for the scientific integrity of the work.

References

[1] Damiani G, Pinnarelli L, Colosimo SC, et al. The effectiveness of computerized clinical guidelines in the process of care: a systematic review. BMC Health Serv Res. 2010;10:2.

[2] Neame MT, Chacko J, Surace AE, et al. A systematic review of the effects of implementing clinical pathways supported by health information technologies. Journal of the American Medical Informatics Association. 2019;26:356–363.

[3] Trivedi MH, Kern JK, Marcee A, et al. Development and implementation of computerized clinical guidelines: barriers and solutions. Methods Inf Med. 2002;41:435–442.

[4] Forsner T, Hansson J, Brommels M, et al. Implementing clinical guidelines in psychiatry: a qualitative study of perceived facilitators and barriers. BMC Psychiatry. 2010;10:8.

[5] Jin Y, Li Z, Han F, et al. Barriers and enablers for the implementation of clinical practice guidelines in China: a mixed-method study. BMJ Open. 2019;9:e026328.

[6] Observational Health Data Sciences and Informatics (OHDSI). The Book of OHDSI [Internet]. 2021 [cited 2022 Jan 13]. Available from: https://ohdsi.github.io/TheBookOfOhdsi/.

[7] Reinecke I, Zoch M, Reich C, et al. The Usage of OHDSI OMOP - A Scoping Review. Stud Health Technol Inform. 2021;283:95–103.

[8] Stefanelli M. Knowledge and process management in health care organizations. Methods Inf Med. 2004;43:525–535.

[9] Object Management Group. Business Process Model and Notation (BPMN): Version 2.0 [Internet]. 2011 [cited 2022 Jan 13]. Available from: https://www.omg.org/spec/BPMN/2.0/PDF.

[10] Duske, Müller R, Prüfer R, et al. A BPMN Model of the Charite Stroke Treatment Process. Informatik-Berichte 244. 2014.

[11] Sooter LJ, Hasley S, Lario R, et al. Modeling a Clinical Pathway for Contraception. Appl Clin Inform. 2019;10(5):935-943.

[12] Gruhl M, Reinecke I, Sedlmayr M. Specification and Distribution of Vocabularies Among Consortial Partners. Stud Health Technol Inform. 2020;270:1393–1394.

[13] Medical Informatics Initiative Germany (MI-I). The Medical Informatics Initiative's core data set [Internet]. [cited 2022 Jan 13]. Available from: https://www.medizininformatik-initiative.de/en/medical-informatics-initiatives-core-data-set.

[14] Camunda Modeler [Internet]. [cited 2022 Jan 13]. Available from: https://camunda.com/products/camunda-platform/modeler/.

[15] Glicksberg BS, Oskotsky B, Thangaraj PM, et al. PatientExploreR: an extensible application for dynamic visualization of patient clinical history from electronic health records in the OMOP common data model. Wren J, editor. Bioinformatics. 2019;35:4515–4518.

[16] Zhang X, Wang L, Miao S, et al. Analysis of treatment pathways for three chronic diseases using OMOP CDM. J Med Syst. 2018;42:260.

[17] Kim H, Yoo S, Jeon Y, et al. Characterization of Anti-seizure Medication Treatment Pathways in Pediatric Epilepsy Using the Electronic Health Record-Based Common Data Model. Front Neurol. 2020;11:409.

[18] Kalenkova A, Polyvyanyy A, Rosa ML. Structural and Behavioral Biases in Process Comparison Using Models and Logs. In: Ghose A, Horkoff J, Silva Souza VE, et al., editors. Conceptual Modeling [Internet]. Cham: Springer International Publishing; 2021 [cited 2022 Jan 18]. p. 62–73. Available from: https://link.springer.com/10.1007/978-3-030-89022-3_6.