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Appendix: Content Summaries of Selected Best Papers for the 2017 IMIA Yearbook, Section Decision Support

Lin FP, Pokorny A, Teng C, Dear R, Epstein RJ
Computational prediction of multidisciplinary team decision-making for adjuvant breast cancer drug therapies: a machine learning approach
BMC Cancer 2016 Dec 1;16(1):929

Decisions about cancer management rely on the combined expertise of different cancer

specialists and are currently made during multidisciplinary team (MDT) meetings. This collective expertise is however non transferable between centers as a computational tool. The objective of this work is to design a predictive model of MDT decisions using machine learning techniques. The study focused on decision-making for adjuvant breast cancer therapies, i.e. the therapeutical decision after surgery, restricted to drug treatment. A cohort of 1,065 retrospective MDT decisions made in a single oncology department of an Australian hospital over an 8-year period (2007-2015) was collected. MDT decisions were considered with respect to the three modalities of systemic treatments: chemotherapy, endocrine therapy, and targeted therapy. For each modality, the outcomes of the MDT decision were either recommended, non recommended, or discussable. Each decision context was described by the clinical and pathological characteristics of the patient and the tumor at the decision time. Eighteen methods, based on 10 supervised machine learning classifiers, were trained using stratified ten-fold cross-validation for the prediction of MDT decision outcomes. Additionally, predictions were also computed for widely recognized cancer guidelines (ESMO and NCCN). For the employed dataset, results evidenced the best classifiers as those which accurately predicted the three MDT decision outcomes, using ten-fold cross validation. Considering guideline-based predictions, there was no significant difference with MDT decisions of endocrine therapy and targeted therapy. However, for chemotherapy decisions, the difference between guideline-based prediction and MDT decisions was significant and machine learning methods performed better. The authors suggested that these discrepancies for adjuvant chemotherapy might be explained by hidden, non clinicopathologic criteria, like patient preferences and resource availability, taken into account by MDT clinicians, which are captured by learning models, but not considered in guidelines.

Marco-Ruiz L, Pedrinaci C, Maldonado JA, Panziera L, Chen R, Bellika JG
Publication, discovery and interoperability of Clinical Decision Support Systems: A Linked Data approach
J Biomed Inform 2016 Aug;62:243-64

This study introduced a comprehensive paradigm for publication, discovery, and interoperability of CDSSs by employing the linked-data approach. Having their basis on the Service-oriented Architecture (SOA), linked services represent the evolution of the Semantic Web Services paradigm to process linked data. The authors provided extensive background information regarding the technical aspects which are part of their framework, as well as the technological challenges in comparison with existing CDS standards. In particular, the proposed approach entails semantics at four levels, i.e. functional, data, execution, and non-functional semantics. The definition of linked services for CDS involves the description of the service with a Web service modeling ontology and the development of ontologies to attach non-functional, functional, and clinical data semantics to service descriptions. Thus, the creation of the proposed semantic framework of interoperable CDS services relies on the models that the authors defined, comprising machine interpretable ontologies in compliance with linked-data principles. The constructed models were bound to SNOMED-CT and publicly available ontologies. These ontologies facilitate the discovery and analysis of CDS services through automated reasoning. The study illustrated the proposed approach by implementing a set of CDS artifacts as linked services. For expressing these CDS artifacts, openEHR archetypes and Guideline Definition Language rules were employed along with the appropriate terminology bindings. The authors envision the use of the proposed approach inside medium-large health networks that aim to decouple CDS functionalities from the EHR, while CDS services would be offered to any Clinical Information System in the network that requires its functionality based on a shared local knowledge base.

McEvoy DS, Sittig DF, Hickman TT, Aaron S, Ai A, Amato M, Bauer DW, Fraser GM, Harper J, Kennemer A, Krall MA, Lehmann CU, Malhotra S, Murphy DR, O'Kelley B, Samal L, Schreiber R, Singh H, Thomas EJ, Vartian CV, Westmorland J, McCoy AB, Wright A

Variation in high-priority drug-drug

interaction alerts across institutions and electronic health records

J Am Med Inform Assoc 2017 Mar 1;24(2):331-8

This study assessed the variation in high-priority drug-drug interaction (DDI) alerts across a number of diverse EHR systems operating in different healthcare institutions in the US. The main questions posed in the study concerned whether there is a standard of care regarding high-priority DDI alert implementation that spans institutions and EHRs, what impact EHR vendors have on DDI alert implementation and display, and what impact healthcare organizations have on DDI alert implementation and display. The material for conducting the study relied on 15 drug pairs approved by an expert panel as “contraindicated for concurrent use” and that should “always be alerted on”. They were used as a standard for implementation across EHR systems. For each DDI pair, the following information was recorded: a) the presence of an alert; b) the alert severity level; c) the alert display; d) the passive alert appearance, e) the override capability, and f) the override reason requirement. Seventeen medical informaticians completed the evaluation of their CPOE/EHR system, while two freely available EHRs were also evaluated. The findings of the study include: a) no system alerted on all of the DDI pairs tested; b) across all systems, 58% of the DDI pairs produced interruptive alerts, while an additional 12% produced passive alerts; c) a

great variation in alert display across systems was recorded; d) in one system, all alerts were interruptive, while in another system, all alerts were passive; e) only one system used hard stops, which were applicable in seven of the DDIs evaluated, and f) EHR vendors and DDI definition repositories differed across systems, but nearly all systems had different severity levels of DDI alerts available. In view of the original questions posed, the study concluded with two relevant recommendations: a) healthcare institutions shall carefully review their DDI alerting approaches, and b) there is a need for creating an officially approved, standardized DDI reference resource by a national or international committee comprising all relevant stakeholders.

Zamborlini V, Hoekstra R, Da Silveira M, Pruski C, ten Teije A, van Harmelen F

Inferring recommendation interactions in clinical guidelines

Semantic Web 2016;7(4):421-46

The management of multimorbidities is a growing concern in medical practice. Clinical practice guidelines provide recommendations for single diseases, as does their computerized version in decision support systems. In case of multimorbid patients, guideline-based recommendations issued for each pathology may interact, and possibly be conflicting. A unique modeling framework to represent clinical guidelines is proposed to allow for the reuse

and combination of knowledge from multiple guidelines. The formal model to represent guidelines, named TMR4I (Transition-based Medical Recommendations for detecting Interactions), is based on the descriptions of a) ‘actions’, like drug prescriptions, b) ‘transitions’ between a current state and an expected state through an ‘action’, and c) ‘recommendations’ to perform or not a ‘transition’. Logical descriptions of different types of interactions between recommendations are specified. These interactions may be internal, within the same guideline, or external, between distinct guidelines. Semantic web technologies (mainly ontologies and rules) as well as the possibility to access linked data about DDIs were used to implement a prototype that automatically infers recommendation interactions. This framework has been tested on two realistic cases on the multimorbidity management extracted from prior works published by different authors that address the same topic to allow for comparisons. The first case combines two guidelines for Duodenal Ulcer and Transient Ischemic Attack. The second case mixed three guidelines for Osteoarthritis, Hypertension, and Diabetes, respectively. In this work, the detection of interactions between recommendations is performed during the knowledge modeling phases and not at the execution time, i.e. without any given patient case. The overall framework is generic, as well as not restricted to specific guidelines, or to their number.