community. OBJECTIVES/GOALS: REDCap is a clinical research data collection platform that is primarily used as intended. However, little is known about its more novel uses, specifically in clinical decision support in patient care and in clinical research management. Thus, the purpose of this review is to examine peer reviewed literature identifying and describing such novel uses. METHODS/STUDY POPULATION: A systematic search was conducted in both PubMed and Google Scholar using the equation ((REDCap) OR ('Research Electronic Data Capture')) AND ((Clinical Trial Management) OR (Clinical Research)).' Articles were screened by title, then abstract, and then were reviewed in full if they met inclusion criteria. Articles were included if they had potential relevance to the topic of REDCap or if they mentioned activities related to fields of clinical and translational science including operational support in areas such as clinical research management. Articles were excluded if they focused on common clinical research activities relating to data collection software such as survey administration, database building or data collection for clinical trials, registries, and cohort studies. RESULTS/ANTICIPATED RESULTS: The initial search yielded 390 results, of which 40 underwent an abstract review; only 8 of these underwent full text review. Of these, 5 discussed uses of REDCap in the context of operational support in clinical research management; 3 were related to clinical decision support in patient care. For the 5 articles focused on operational support in clinical research management, topics include e-consenting procedures, collection and storage of protected health information (PHI), patient recruitment and tracking stakeholder engagement. The 3 articles about clinical decision support discuss REDCap tools for generating risk predictions for post-surgical clinical outcomes, generating recommendations and STI test orders, and increasing efficiency in hand-offs to enhance care of surgical oncology patients. DISCUSSION/SIGNIFICANCE OF FINDINGS: Considering that only a small percentage of peer reviewed research reports out on novel uses of REDCap, there is a need for the REDCap consortium to do further work to fulfill its mission to adopt, innovate, and suggest novel uses of REDCap, thus expanding the understanding of its functionalities and therefore its utility in the research community.

41250

Machine Learning to Identify Predictors of Iatrogenic Injury Using Empirical Bayes Estimates: A Cohort Study of Pressure Injury Prevention

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ABSTRACT IMPACT: A machine learning approach using electronic health records can combine descriptive, population-level factors of pressure injury outcomes. OBJECTIVES/GOALS: Pressure injuries cause 60,000 deaths and cost $26 billion annually in the US, but prevention is laborious. We used clinical data to develop a machine learning algorithm for predicting pressure injury risk and prescribe the timing of intervention to help clinicians balance competing priorities. METHODS/STUDY POPULATION: We obtained 94,745 electronic health records with 7,000 predictors to calibrate a predictive algorithm of pressure injury risk. Machine learning was used to mine features predicting changes in pressure injury risk; random forests outperformed neural networks, boosting and bagging in feature selection. These features were fit to multilevel ordered logistic regression to create an algorithm that generated empirical Bayes estimates informing a decision-rule for follow-up based on individual risk trajectories over time. We used cross-validation to verify predictive validity, and constrained optimization to select a best-fit algorithm that reduced the time required to trigger patient follow-up. RESULTS/ANTICIPATED RESULTS: The algorithm significantly improved prediction of pressure injury risk ($p<0.001$) with an area under the ROC curve of 0.60 compared to the Braden Scale, a traditional clinician instrument of pressure injury risk. At a specificity of 0.50, the model achieved a sensitivity of 0.63 within 2.5 patient-days. Machine learning identified categorical increases in risk when patients were prescribed vasopressors (OR=16.4, $p<0.001$), beta-blockers (OR=4.8, $p<0.001$), erythropoietin stimulating agents (OR=3.0, $p<0.001$), or were ordered a urinalysis screen (OR=9.1, $p<0.001$), lipid panel (OR=5.7, $p<0.001$) or pre-albumin panel (OR=2.0, $p<0.001$). DISCUSSION/SIGNIFICANCE OF FINDINGS: This algorithm could help hospitals conserve resources within a critical period of patient vulnerability for pressure injury not reimbursed by Medicare. Savings generated by this approach could justify investment in machine learning to develop electronic warning systems for many iatrogenic injuries.

67409

Quantifying Unmeasured Confounding in Relationship between Treatment Intensity and Outcomes among Older Patients with Hodgkin Lymphoma (HL) using Surveillance, Epidemiology and End Results (SEER)-Medicare Data

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ABSTRACT IMPACT: E-values can help quantify the amount of unmeasured confounded necessary to fully explain away a relationship between treatment and outcomes in observational data. OBJECTIVES/GOALS: Older patients with HL have worse outcomes than younger patients, which may reflect treatment choice (e.g., fewer chemotherapy cycles). We studied the relationship between treatment intensity and 3-year overall survival (OS) in SEER-Medicare. We calculated an E-value to quantify the unmeasured confounding needed to explain away any relationship. METHODS/STUDY POPULATION: This retrospective cohort study of SEER-Medicare data from 1999-2016 included 1131 patients diagnosed with advanced stage HL at age ≥65 years. Treatment was categorized as: (1) full chemotherapy regimens ('full regimen', n=689); (2) partial chemotherapy regimen ('partial regimen', n=175); (3) single chemotherapy agent or radiotherapy ('single agent/RT', n=102), or (4) no treatment (n=165). A multivariable Cox regression model estimated the relationship between treatment and 3-year OS, adjusting for disease and patient factors. An E-value was computed to quantify the minimum strength of association that an unmeasured confounder would need to have with both the treatment and OS to completely explain away a significant association between treatment and OS based on the multivariable model. RESULTS/ANTICIPATED RESULTS: Results from the multivariable model found higher hazards of death for partial regimens (HR=1.81, 95% CI=1.43, 2.29), single agent/RT (HR=1.74, 95% CI=1.30, 2.34), or no treatment (HR=1.98, 95% CI=1.56, 2.552) compared to full regimens. We calculated an E-value for single agent/RT because it has the smallest HR of the treatment levels. The observed HR of 1.74 could be explained away by an unmeasured confounder that was associated with both treatment and OS with a HR of 2.29, above and beyond the measured confounders; the 95% CI could be moved to include the null by an unmeasured confounder that was associated with both the treatment and OS with a HR of 1.69. Of the

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