PD17 Automating The Impact Reporting Of NICE Guidance

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Introduction. The National Institute for Health and Care Excellence (NICE) intends to automate the way it monitors the uptake, impact, and value of its guidance. Traditionally this has been done by developing impact reports, long documents that, while well received, are time consuming to develop and can quickly become outdated.
Methods. We focused on a novel topic that would benefit from new data sources to examine its impact: a rapid guideline for managing the long-term effects of coronavirus disease 2019 (COVID-19). We shortlisted "measurable" recommendations within the guideline that were likely to be captured in data collections. We then reviewed available data sources that included relevant up-to-date data. Finally, we explored what existing methods were available to NICE for automating impact reporting.
Results. For long COVID-19 we accessed OpenSAFELY, a secure, transparent software platform for primary care COVID-19 data that was developed in response to the pandemic. This captured data on the management of long COVID-19 in primary care as well as onward referral to specialist clinics. In addition, we accessed data from the CVD-COVID-UK/COVID-IMPACT Consortium, which links general practice records with primary care dispensing data. This enabled us to analyze the impact of the pandemic on the prescribing and dispensing of cardiovascular disease medications. Working with our digital team we developed an automated impact reporting dashboard using Google's data studio. This enabled different views of the data, for example by region or socioeconomic status, to be presented in an automated way.
Conclusions. Automating the impact reporting of NICE guidance provides up-to-date information on its value to the health system. While we were able to collect new sources of data and automate some aspects of how these were viewed, full automation requires several enablers. These include an application programming interface between the data sources and NICE, and ensuring that NICE guidance is computer readable so that its measurement is practical in healthcare systems.

PD19 Machine Learning Modelling For Clinical Trial Design Using The National Institute for Health and Care Research Innovation Observatory's ScanMedicine Database

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Introduction. Clinical trials that fail prematurely due to poor design are a waste of resources and deprives us of data for evaluating potentially effective interventions. This study used machine learning modelling to predict clinical trials' success or failure and to understand feature contributions driving this result. Features to power the modelling were engineered using data collected from the National Institute for Health and Care Research Innovation Observatory's ScanMedicine database.
Methods. Using ScanMedicine, a large dataset containing 641,079 clinical trial records from 11 global clinical trial registries, was extracted. Sixteen features were generated from the data based on fields relating to trial design and eligibility. Trials were labeled positive if they were completed (or target recruitment was achieved) or negative if terminated/withdrawn (or target recruitment was not achieved). To achieve optimal performance, phase-specific datasets were generated, and we focused on a subsample of Phase 2 trials (n=70,167). Ensemble models using bagging and boosting algorithms, including balanced random forest and extreme gradient boosting classifiers were used for training and evaluating predictive performance. Shapley Additive Explanations was used to explain the output of the best performing model and calculate feature contributions for individual studies.
Results. We achieved a weighted F1-score of 0.88, Receiver Operator Characteristic Area under the Curve score of 0.75, and balanced accuracy of 0.75 on the test set with the xgBoost model. This result shows that the model can successfully distinguish between classes to predict if a trial will succeed or fail and subsequently output the features driving this outcome. The number of primary outcomes, whether the study was randomized, target sample size and number of exclusion criteria were the most important features affecting the model's prediction.
Conclusions. This study is the first to use predictive modelling on a large sample of clinical trial data obtained from 11 international trial registries. The prediction outcomes achieved by our novel approach, which uses phase-specific trained models, outperforms previous modelling in this space.

PD20 Real-World Evidence To Support Single Arm Trials Of Oncology Interventions: Necessity or 'NICE' (National Institute for Health and Care Excellence) to Have?

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Introduction. The recent National Institute for Health and Care Excellence (NICE) consultation on methods for health technology evaluation (HTE) outlined plans to include guidance on the role of real-world evidence (RWE) in HTE. This is particularly pertinent for interventions where the evidence base consists of a single arm trial (SAT) design, which is more frequently observed in oncology.

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