ARTIFICIAL INTELLIGENCE FOR IMPROVED PATIENT OUTCOMES

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BACKGROUND

- AI's potential in medicine is promising, but there is little rigorous evidence that it improves patient outcomes.
- Most studies lack proper outcome evaluation or have inadequate study design – the RCT is critical for proving that AI can improve patient outcomes.
- AI should assist physicians, not replace them, to improve patient care and reduce physician burnout.
- The last mile is using pragmatic RCTs to measure AI's impact on patient outcomes and then implementing models that have been proven to have an impact on patient outcomes.

WHAT IS NOT WORKING

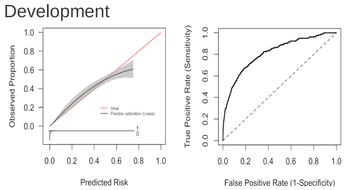
- Most published models are not developed in a way that can be implemented.
- Even fewer are evaluated in a way that can show AI benefits patients.
- It is not enough to develop an accurate model.
- The important question is whether the model/clinician partnership is an improvement over current standard of care.

Study	Operationalizable	Broadly Applicable	Updated	Actionable	Validated	Total Criteria Met
Ende et al. (2022)	●	●	●	●	●	5
Ahmadzia et al. (2018)[4]	●	○	●	●	●	4
Helman et al. (2015)[5]	●	●	●	●	○	4
Rubio-Alvarez et al. (2018)[6]	○	○	●	●	●	3
Albright et al. (2019)[7]	●	○	○	●	●	3
Goad et al. (2021)[8]	○	●	●	○	●	3
Koopmans et al. (2014)[9]	○	○	●	○	●	2
Cortet et al. (2015)[10]	○	○	●	●	○	2
Suta et al. (2015)[11]	○	○	●	●	○	2
Niepraschk-von Dollen et al. (2016)[12]	○	○	●	●	○	2
Kim et al. (2017)[13]	○	○	○	●	●	2
Shinohara et al. (2018)[14]	○	○	●	●	○	2
Venkatesh et al. (2020)[15]	○	●	○	○	●	2
Liu et al. (2022)[16]	○	○	○	●	●	2
Prata et al. (2011)[17]	○	○	●	○	○	1
Chen et al. (2011)[18]	○	●	○	○	○	1
Biguzzi et al. (2012)[19]	○	○	●	○	○	1
Yoon et al. (2014)[20]	○	○	○	●	○	1
Baba et al. (2015)[21]	○	○	○	●	○	1

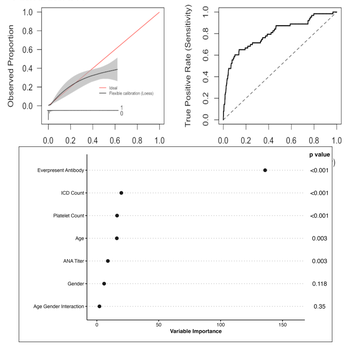
MODEL BUILDING APPROACH

- Model agnosticism: use the best tool for the job. Fit multiple models and compare.
- 80/20 temporal validation split using single data pull. No 50/50 forced balancing.
- Prespecify clinically relevant predictors in the model and avoid reverse causation - automated variable selection results can result in pitfalls.
- Use bootstrapping for parameter optimization and model validation using all candidate predictors.

Development

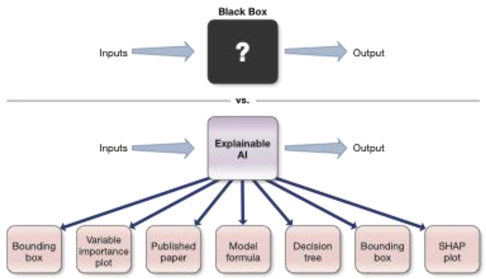


Validation

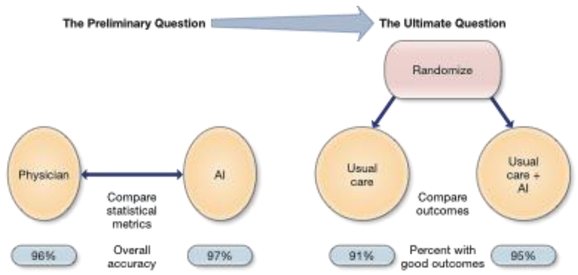


MODEL IMPLEMENTATION

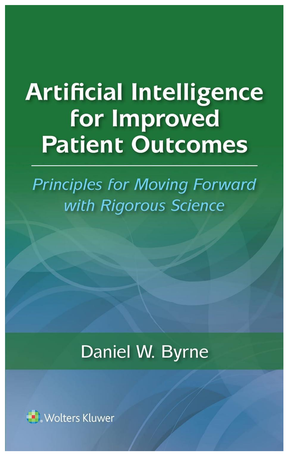
VTE Risk (%)	Medication	DVT Indicator
77		x
66.5	x	
54.5		
34.5		
27.7	x	
26.7		
25.9		
24.3		
22.3	x	
22.2		
21.1		



PRAGMATIC MODEL EVALUATION

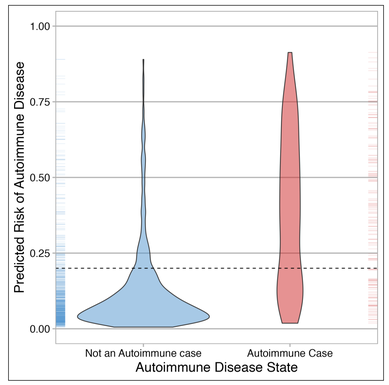


- The RCT is critical for evaluating efficacy of the intervention – would not implement a drug without a clinical trial
- RCT evaluates clinically relevant patient-centered outcomes, not model performance.
- Before/After evaluations are prone to regression to the mean, confounding bias, and contribute to alert fatigue.
- Patient-level RCTs can be designed to fit seamlessly into workflow.
- Data from RCT allow us to see what is/is not working, improve the intervention, and gain valuable data even when trial is negative.



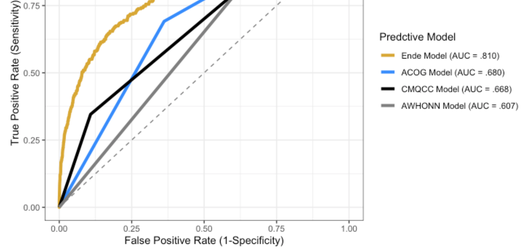
AUTOIMMUNE DISEASE RISK PREDICTION

- Positive antinuclear antibodies (ANAs) cause diagnostic dilemmas.
- First-of-its-kind autoimmune disease risk model for ANA positive patients, seamlessly integrated into EHR and undergoing pragmatic RCT.
- Recommendation for expedited rheumatology consult for high-risk patients.



POSTPARTUM HEMORRHAGE PREDICTION

- Postpartum hemorrhage the leading cause of maternal death globally
- Developed and validated modernized predictive model for PPH
- Currently undergoing evaluation at an external site and with a pragmatic RCT



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Shiny Application

Artificial Intelligence for Improved Patient Outcomes Book