Change in machine learning model performance upon retraining after deployment into clinical practice: The real-world effect of model predictions on clinician actions, outcome labels, and the potential for contamination bias

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BACKGROUND

CHARTWatch is an AI model that was implemented at St. Michael's Hospital in October 2020 and predicts inpatient deterioration on medical wards.[1]

AI Models may degrade over time due to factors like data drift and may require retraining. However, retraining a deployed model using post-deployment data may worsen performance due to **contamination bias**—a phenomenon where the model changes outcomes it later uses to retrain, as shown in recent simulation studies.[2-5]

To inform whether to retrain CHARTwatch, we sought to **quantify the degree of contamination bias** and explore strategies to mitigate it.

METHODS

Part 1: Prospective cohort study

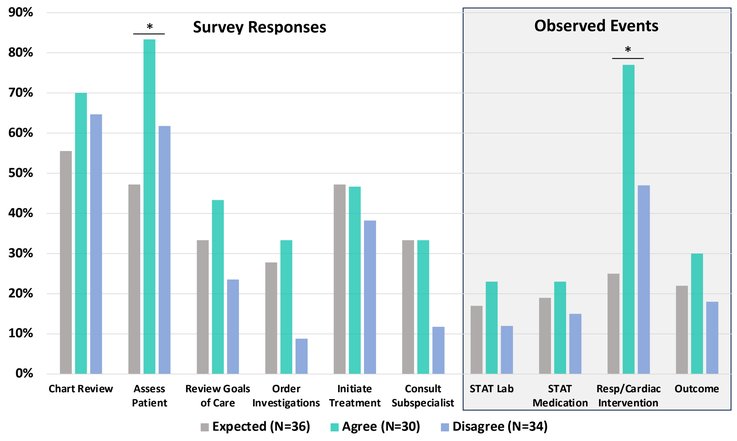
- Evaluate how often CHARTwatch prevents patient deterioration (effective intervention rate) through real-time surveys and chart review for 100 consecutive alerts
- Quantify the overall outcome frequency and model recall

Part 2: Model retraining evaluations

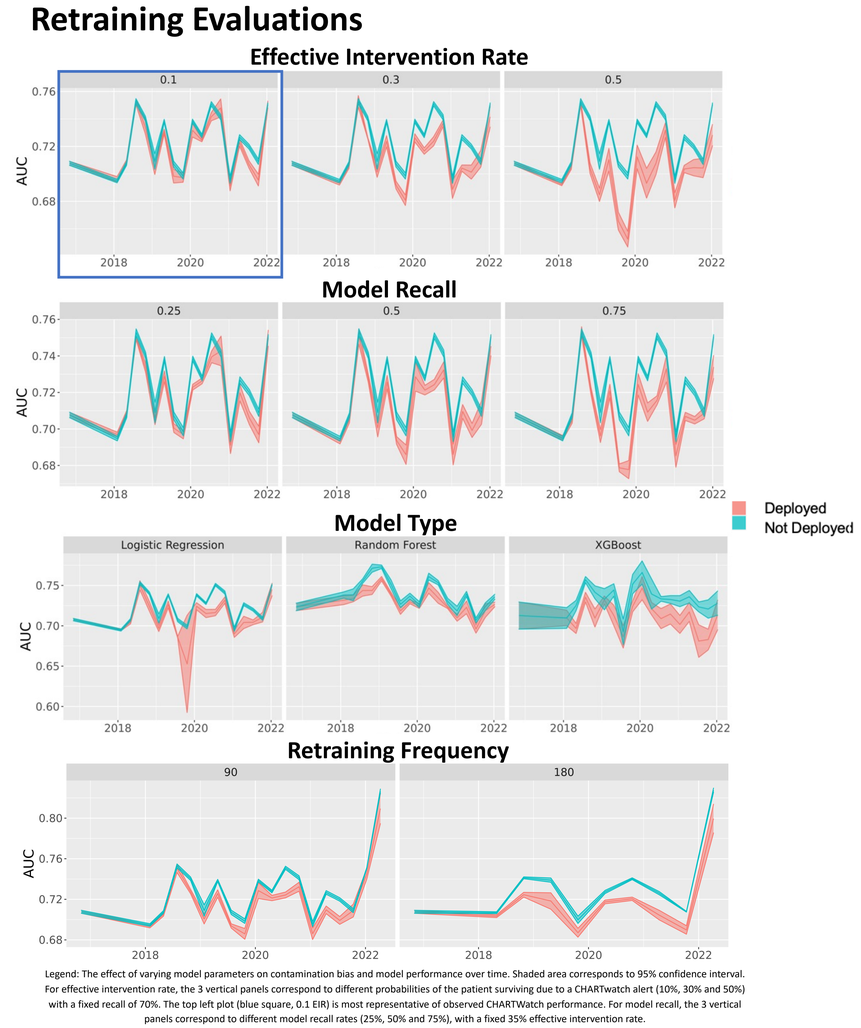
- Evaluate the change in model performance due to contamination bias when retraining with a range of effective intervention rates , recall frequencies, and ML model types, with values informed by the prospective cohort study
- Contamination bias mitigation: Evaluate the effect of removing potentially confounded outcomes prior to retraining on the magnitude of contamination bias and overall model performance

RESULTS

Prospective Cohort Study

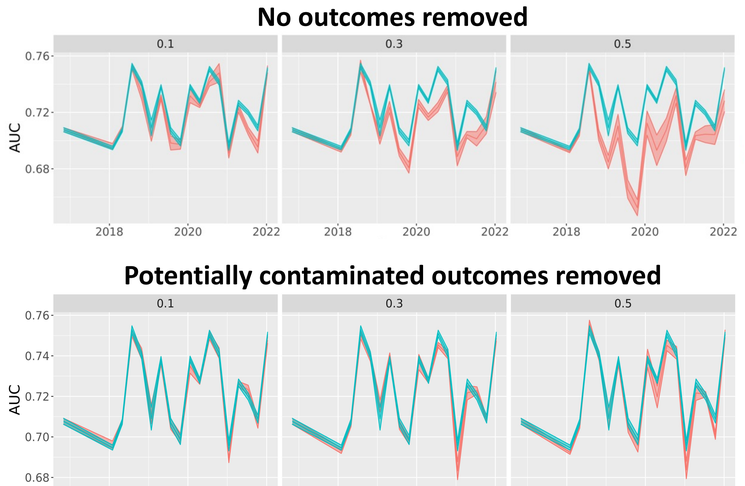


Retraining Evaluations



Legend: The effect of varying model parameters on contamination bias and model performance over time. Shaded area corresponds to 95% confidence interval. For effective intervention rate, the 3 vertical panels correspond to different probabilities of the patient surviving due to a CHARTwatch alert (10%, 30% and 50%) with a fixed recall of 70%. The top left plot (blue square, 0.1 EIR) is most representative of observed CHARTWatch performance. For model recall, the 3 vertical panels correspond to different model recall rates (25%, 50% and 75%), with a fixed 35% effective intervention rate.

Contamination Bias Mitigation



Legend: The effect of removing potentially contaminated outcomes before retraining on model performance over time. Shaded area corresponds to 95% confidence interval. In the top panel, all patient outcomes were retained in model retraining. In the bottom panel, for the deployed model, all patients who had a CHARTwatch alert but did not experience an outcome were removed from retraining as they were potentially contaminated. The three vertical panels correspond to model effective intervention rates of 10%, 30% and 50%.

DISCUSSION

Clinician agreement with CHARTwatch predictions is associated with downstream clinical actions.

We present a framework for using clinician perception/actions and model parameters to estimate contamination bias.

For CHARTwatch, contamination bias at any retraining interval is limited (△AUC <2%) but the impact over time is summative.

Removing potentially confounded outcomes may help mitigate contamination bias during retraining.

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