Methods

• All ICD-9 and ICD-10 codes were mapped to ICD-10CPS equivalents.
• All ICD-9CM and ICD-10CM diagnoses were mapped to SNOMED equivalents.
• Only the XGBoost model was built on the "full dataset," comprising all 20M meta-visits.
• XGBoost, Logistic Regression, Random Forest Decision, and LinearSRV were trained and tested on a smaller "Balanced dataset" comprising all 83,113 class 1 "meta-visits and a randomly selected 83,113 class 0 "meta-visits, for a total of 166,226 meta-visits.
• To validate ML models and to verify we were not overfitting, multiple approaches were used. (Figure 1): 1. "Person-model": to ensure we had no within-person information leakage was occurring. 2. "Validation-model": to confirm classification performance was not due to overfitting. 3. "Mislabeled-data-model" and "Mislabeled-full-data-model": to validate recovery of uncoded self-harm. 4. "Coding-bias-model": to find which variables were associated with high certainty imputed self-harm cases not being coded. 5. "Full-factorial-models": to determine the classes of covariates that contributed most to the classification performance of ML models. 6. "Gold Standard": to validate the ML models by using the classification of 3 clinicians. Detailed comparisons of coded versus imputed self-harm incidence were made by patient age, sex, MMI category, and US state of residence.

Results

• Selected 20M meta-visits had 6,037,479 unique patients (31.9% males and 68.1% females).
• The XGBoost "Full-data-model" probabilities of self-harm (Class "1") summed to 1,592,703 (7.66%).
• Overall imputed annual incidence was 5.34%, whereas the coded annual incidence was 0.28%.
• Out of 83,113, meta-visits coded for self-harm, 79,882 (96.11%) had class 1 "probability >0.5 and 62,929 (75.71%) had class 1 "probability ≥0.95.
• Out of 185,234 meta-visits used to build the "Full-data-model," only 2,205 (1.19%) had relative gain >0.
• The XGboost "Full-data-model" probabilities of self-harm (Class "1") summed to 1,592,703 (7.66%).
• The pairwise agreement between the XGboost "Full-data-model" probabilities of self-harm (Class "1") was 56.4% ± 2×10^-4.
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Conclusions

• Only about 1 in 19 self-harm events were reported in US claims data among patients with MMI.
• ML methods effectively infer unreported self-harm events.
• The underreporting of self-harm varied by sex and age, suggesting potential coding bias.
• Self-harm undercoding steadily increased with age.
• Self-harm incidence varied considerably by gender, age, and among MMI categories.

References