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Developing computable phenotypes for cardiometabolic risk factors in the eMR: the SPEED-EXTRACT study

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Background
Computable phenotypes are clinical conditions determined from data in electronic medical records (eMR). They enable real-time identification of patient characteristics, which is not possible with administrative data (e.g., manually coded ICD10).

Objectives
We evaluated the feasibility of computable phenotypes for cardiometabolic risk factors in Northern Sydney Local Health District eMR, and compared the results with administrative ICD10 codes.

Method
Data from the eMR was extracted from >30K presentations of chest-pain to NSLHD emergency departments between 1st April to 30th June, 2017. Computable phenotypes determined the presence of five risk factors: diabetes, hypertension, hyperlipidemia, smoking and obesity. Clinical data sources included pathology results (HbA1c), assessments (body mass index), medications and medical notes (eg. prior medical history, risk factors).

Results
103 ICD10 coded STEMI patients (77 males; mean age 67y) were included in the preliminary analysis. Missing data was present, however phenotyping for diabetes, hypertension and hyperlipidemia was possible in 100% of patients. Smoking and obesity were 66% and 52% complete. Using clinical sources, the estimated prevalence of diabetes and smoking was lower than ICD10 codes indicated: Diabetes 13% vs 19%; Smoking 12% vs 23%. In contrast, the prevalence of hypertension, hyperlipidemia, and obesity were much higher than ICD10: hypertension 86% vs 20%; hyperlipidemia 73% vs 7%; obesity 33% vs 18%.

Conclusions
Data availability in the eMR was incomplete, but phenotyping was feasible in the majority of cases as disparate and diverse data sources can be accessed. Overall, our pilot data supports the feasibility of a computational framework in this setting, along with optimisation of definitions to account for variations in local settings.