International Journal of Cardiology 187 (2015) 705–711

Contents lists available at ScienceDirect

International Journal of Cardiology

journal homepage: www.elsevier.com/locate/ijcard

Review

Use of electronic health records to ascertain, validate and phenotype acute myocardial infarction: A systematic review and recommendations

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ARTICLE INFO

Article history:
Received 15 December 2014
Received in revised form 16 February 2015
Accepted 3 March 2015
Available online 5 March 2015

Keywords:
Electronic health records
Myocardial infarction
Acute coronary syndrome
Validation studies
Phenotype
Clinical coding

ABSTRACT

Electronic health records (EHRs) offer the opportunity to ascertain clinical outcomes at large scale and low cost, thus facilitating cohort studies, quality of care research and clinical trials. For acute myocardial infarction (AMI) the extent to which different EHR sources are accessible and accurate remains uncertain.

Using MEDLINE and EMBASE we identified thirty three studies, reporting a total of 128 658 patients, published between January 2000 and July 2014 that permitted assessment of the validity of AMI diagnosis drawn from EHR sources against a reference such as manual chart review. In contrast to clinical practice, only one study used EHR-derived markers of myocardial necrosis to identify possible AMI cases, none used electrocardiogram findings and one used symptoms in the form of free text combined with coded diagnosis. The remaining studies relied mostly on coded diagnosis. Thirty one studies reported positive predictive value (PPV) ≥ 70% between AMI diagnosis from both secondary care and primary care EHRs and the reference. Among fifteen studies reporting EHR-derived AMI phenotypes, three cross-referenced ST-segment elevation AMI diagnosis (PPV range 71–100%), two non-ST-segment elevation AMI (PPV 91.0, 92.1%), three non-fatal AMI (PPV range 82–92.2%) and six fatal AMI (PPV range 64–91.7%).

Clinical coding of EHR-derived AMI diagnosis in primary care and secondary care was found to be accurate in different clinical settings and for different phenotypes. However, markers of myocardial necrosis, ECG and symptoms, the cornerstones of a clinical diagnosis, are underutilised and remain a challenge to retrieve from EHRs.

1. Introduction

Information on clinical diagnoses and outcomes derived from electronic health records (EHRs) is of increasing relevance for both clinicians and researchers [1]. These records represent a rich source of clinical information, collected at minimal cost, in large numbers of people and with potential for linkage to other data sources [2]. Acute myocardial infarction (AMI) represents an important clinical outcome, and unlike many diseases, has internationally accepted and well-defined diagnostic criteria which are widely used in clinical practice [3]. EHRs have been used in different types of research: to assess quality and performance of healthcare providers for managing patients [4,5], to monitor national trends in mortality and morbidity, along with intra and inter-country comparisons of healthcare policy [6] and to generate outcome data for prospective studies and clinical trials [7–10]. There is a growing interest in EHR phenotypes to gain insights into the aetiology of AMI through "omic" association studies [11].

However there have been no systematic, contemporary evaluations of the diverse sources of EHR data relevant for AMI ascertainment, and of the validity of EHR data on AMI. In this context, EHRs encompass any electronic source of information relevant to the definition of AMI, including hospital EHRs containing clinical details such as markers of myocardial necrosis values, electrocardiogram (ECG) data, and administrative data on diagnoses used for billing purposes; registries (including disease and mortality registries); and primary care EHRs.

We sought to (1) evaluate the extent to which electronically stored information on markers of myocardial necrosis, ECG findings, symptoms and diagnoses has been used to ascertain AMI, (2) evaluate the accuracy of such EHR information, in different clinical settings, countries and for different phenotypes and (3) make recommendations where improvements are required. In order to do so, we carried out a systematic review of contemporary studies according to MOOSE [12] and PRISMA [13] guidelines.

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http://dx.doi.org/10.1016/j.ijcard.2015.03.075

2. Methods

2.1. Search strategies

We searched MEDLINE and EMBASE databases for studies reporting on EHR-derived AMI diagnosis published between 1 January 2000 and 31 July 2014. Keywords for EHRs, AMI, sensitivity, specificity, positive predictive value (PPV), markers of myocardial necrosis and ECG were searched using Medical Subject Headings (MeSH) terms and combined using Boolean operators as appropriate (Supplementary material online, Appendix A).

2.2. Inclusion criteria

Eligible studies (1) were published after the year 2000; (2) ascertained information relevant to an AMI diagnosis available in EHRs; (3) compared EHR data with manual chart review, or other relevant information; and, (4) provided or had a calculable PPV ('true' diagnosis of AMI in reference/all AMI diagnosed in EHRs). Where available, we report the sensitivity and specificity.

The medical classification systems used to identify AMI diagnosis were International Classification of Diseases revision 8 (ICD-8), ICD-9 (-CM, Clinical Modification) [14] or ICD-10, Diagnosis-related Group (DRG) [15], Current Procedural Terminology (CPT) [16], and in primary care Read Codes [17] and International Classification of Primary Care (ICPC) [18]. Studies using unstructured data (free text) were also included and studies published in a foreign language with an abstract in English were translated by a native speaker.

2.3. Study screening and data extraction

Two authors (BR and NKF) independently reviewed all abstracts for eligibility and obtained full text studies where inclusion criteria were met or there was uncertainty. Studies were excluded when both reviewers agreed the inclusion criteria were not met and conflicts were resolved by discussion with a third author (RSP) to reach consensus. Additional studies were identified by hand-searching reference lists. BR and NKF extracted quantitative and qualitative data from eligible studies. Multiple publications from one study dataset were deemed eligible where results were reported for two or more AMI phenotypes.

2.4. Quantitative and qualitative measurements

Accuracy of AMI diagnosis in an EHR source compared to a reference was assessed by PPV, which we defined arbitrarily as high if equal to or above 90% and moderate if between 70 and 89%. The Wilson method for binomial proportions [19] was used in STATA 13.1 to calculate 95% confidence intervals (CI) for studies that did not report it. For calculated values, decimal places were only reported when study sample sizes (n) were equal to or above 200. Eleven quality criteria adapted from a standardised checklist [13] were used to evaluate the quality of studies included in this review (Supplementary material online, Appendix B).

3. Results

The initial search strategy identified 2561 abstracts (Supplementary material online, Appendix C). After excluding duplicates, 1862 abstracts were reviewed for eligibility, with thirty three studies meeting the full inclusion criteria, three of which were published in a foreign language (Supplementary material online, Appendix D). A total of 128 658 EHR-derived AMI diagnosis were identified and cross-referenced, of which 18 164 potential cases were validated using manual chart review.

3.1. Clinical data features used for ascertainment and validation of AMI

Studies were grouped into three different groups according to the EHR source from which AMI diagnosis was derived, with twenty three studies cross-referencing AMI diagnosis from secondary care, four from mortality registries and three from primary care. Despite being collected and used for different purposes, studies using administrative billing databases (13/23) and hospital databases (10/23) to identify AMI diagnosis in secondary care EHRs were grouped together because AMI diagnosis was mostly derived using the same clinical data feature (ICD-coded diagnosis).

Only one study cross-referenced EHR-derived abnormal troponin levels with ICD-9 coded diagnosis [20]. None of the studies used electronically stored ECG data (digital wave form, computer interpretation or physician interpretation), while one used symptoms in the form of free text, combined with coded diagnosis, to search EHR sources for AMI cases ($n = 213$) [21]. Heriot et al. also used unstructured data to search for AMI diagnosis in electronic databases ($n = 48$) and compared these with post-mortem diagnosis obtained from autopsy reports [22]. Remaining studies relied on a mixture of structured data from coded admission and/or discharge diagnosis and death certificates (Fig. 1).

Chart review was the preferred reference against which EHR-derived AMI diagnosis was compared (24/33), despite five studies reporting concerns over the lack of completeness of medical charts. Other references included disease and mortality registries, questionnaires sent to general practitioners, autopsy findings and computerised algorithms based on information obtained from medical charts (Supplementary material online, Appendix E). Twenty nine studies obtained cross referencing information on markers of myocardial necrosis, twenty five on ECG findings and twenty one on clinical symptoms.

'True' AMI status was mostly based on the WHO MONICA [23] criteria (10/33), or the Joint European Society of Cardiology (ESC)/American College of Cardiology (ACC) Committee [24] and American Heart Association (AHA) Council on Epidemiology and Prevention [25] criteria (9/33). Other criteria are listed on the Supplementary material online, Appendix E.

3.2. Algorithms used to define EHR-derived AMI diagnosis

Studies used a range of coding algorithms to ascertain AMI diagnosis in EHRs. Eighteen studies confined the search to ICD-10 code I21 and/or ICD-9 code 410, four combined those with codes for subsequent acute myocardial infarction (ICD-10 code I22 or ICD-9 code 412), while five also used other forms of acute ischaemic heart disease (ICD-9 codes 411, 413, 414 or ICD-10 codes I20 and I24) in their search algorithm. Studies that ascertained STEMI and NSTEMI from hospital EHR used algorithms based on a combination of ICD codes to account for the lack of a specific ICD-9 and ICD-10 code for these events (Supplementary material online, Appendix E).

3.3. PPV of AMI diagnosis in EHR sources (Fig. 2)

Twenty three studies ascertained AMI diagnosis from a secondary EHR source against a non-electronic reference. Of those, twenty used chart review as reference and nineteen reported moderate to high PPVs (range 76–100%). Despite observing low PPV (20.7%), Gonski et al. [20] found high sensitivity (100%), specificity (78.4%) and negative predictive value (NPV) (100%) when comparing troponin levels in electronically stored troponin lists to ICD-coded AMI discharge diagnosis derived from chart review. The three studies that did not use chart review as reference observed the lowest PPVs ($\leq$75%). Two used a computerised algorithm based on information extracted by chart review, of which one reported a PPV of 40% [26].

PPVs for the three studies that compared AMI diagnosis in primary care EHRs with a reference varied between 75.0% and 96.6%, while four studies using mortality registries found PPV between 67.1% and