A Systematic Approach to Reconciling Data Quality Failures: Investigation Using Spinal Cord Injury Data

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Abstract

Background  Secondary use of electronic health record’s (EHR) data requires evaluation of data quality (DQ) for fitness of use. While multiple frameworks exist for quantifying DQ, there are no guidelines for the evaluation of DQ failures identified through such frameworks.

Objectives  This study proposes a systematic approach to evaluate DQ failures through the understanding of data provenance to support exploratory modeling in machine learning.

Methods  Our study is based on the EHR of spinal cord injury inpatients in a state spinal care center in Australia, admitted between 2011 and 2018 (inclusive), and aged over 17 years. DQ was measured in our prerequisite step of applying a DQ framework on the EHR data through rules that quantified DQ dimensions. DQ was measured as the percentage of values per field that meet the criteria or Krippendorff’s α for agreement between variables. These failures were then assessed using semistructured interviews with purposively sampled domain experts.

Results  The DQ of the fields in our dataset was measured to be from 0% adherent up to 100%. Understanding the data provenance of fields with DQ failures enabled us to ascertain if each DQ failure was fatal, recoverable, or not relevant to the field’s inclusion in our study. We also identify the themes of data provenance from a DQ perspective as systems, processes, and actors.

Conclusion  A systematic approach to understanding data provenance through the context of data generation helps in the reconciliation or repair of DQ failures and is a necessary step in the preparation of data for secondary use.

Keywords

► data quality  ► electronic health record  ► machine learning modelling  ► trust  ► data quality assessment  ► specialized care

Background and Significance

The widespread adoption of electronic health records (EHRs) has been followed by its adoption as a source of research data in multiple domains,¹–⁴ commonly termed secondary use. The validity and robustness of such secondary use is dependent on the quality of the underlying EHR data, and multiple data quality (DQ) frameworks⁵–⁸ have been articulated for this purpose. These frameworks provide assessment methods for analyzing EHR quality in terms of DQ dimensions.⁹,¹⁰ However, the assessment of DQ remains specific to and dependent on the secondary use case, and this is termed...
“fitness for use.” The failures of a DQ assessment manifest as a typology of challenges documented in the literature such as inconsistencies, missing variables, lack of temporality, and lack of standardization among others. A few of the studies suggest using supplementary data sources, surrogate fields, the Natural Language Processing (NLP) techniques, and shared metadata documentation as possible solutions. Even when a task is well defined and the corresponding DQ dimensions for the assessment of DQ are clear, data are seldom error free. This results in mistrust of the data, and consequently the level of confidence in its viability for research use. This is more relevant for a retrospective study where the data collection and the intended usage do not align as the data usage has possibly been defined some years after the data were stored.

The interpretation of DQ results, when there are DQ failures, is a necessary next step following DQ assessment, but there are no established frameworks that define how such an interpretation can be structured. In this study, we define a systematic approach for the analysis of DQ failures that are surfaced through the application of a DQ framework. DQ is a function of the point in time and context in which it was recorded. An EHR is a collation of data points of differing provenances generated by system users like clinicians and hospital administrators, and recorded for use across multiple systems spanning different care types and facilities. Information generation, storage, and propagation are parts of a dynamic process, and the information transforms as it navigates across departmental boundaries and during the interpersonal communication between stakeholders. Further, when considered retrospectively, the processes that recorded the data could have evolved significantly over the intervening time period, and the generated data reflect this evolution. Thus, the retrospective assessment of DQ failures requires an awareness of not just the information transformation between generation and use but also the dynamics of data generation itself. While the need for such contextual awareness has been studied for dimensions of DQ, an equivalent emphasis on the importance of data provenance in interpreting DQ results is lacking. Data provenance of EHR data is the process of understanding the origin or source of the data, data transformations, and the metadata that provide the underlying context of data generation and collection.

Objectives

The study objective is to develop and describe a systematic approach to assess DQ failures by understanding data provenance and provides guidelines for reconciling or repairing DQ failures by better understanding the context of data generation. The approach is grounded in a study on spinal cord injury (SCI) patients.

Methods

The research is based on longitudinal inpatient EHR data sourced from different care types for SCI patients. The preliminary step in our systematic approach is the quantitative study of DQ of the data using a suitable DQ framework. We then assess the DQ failures by a qualitative study consisting of multiple semistructured interviews with clinicians and data custodians with the objective of understanding the data provenance, and therefore resolve, mitigate, or reconcile the DQ failures revealed during the quantitative study. All analyses were performed using R (3.6.1) and the Multivariate Imputation by Chained Equations (MICE) package.

Guiding Aim

Our secondary use of EHR is exploratory machine learning modeling to discern temporal patterns of complications and infections, so as to identify subgroups of the high-cost and high-need SCI patients. The creation of a comprehensive and sequential record of each SCI patient requires unification from heterogeneous data sources, as they are typically admitted for multiple months at a time, and their medical records necessarily span multiple care types, wards, and laboratories. DQ evaluation would be required to ensure unbiased data. We hypothesized that while the DQ evaluation would identify quality failures, we would need to evaluate these failures through an understanding of data provenance to ascertain if the failure was fatal, recoverable, or not relevant to the field’s inclusion in our dataset.

Data

The research analyses the DQ of EHR representing the medical records of SCI patients at Austin’s State Spinal Centre. We define EHR to be inpatient data retrieved from data warehouse, care type data silos, external registries and diagnosis recording (International Classification of Diseases, 10th revision Australian Modification (ICD)-10 AM coding). The cohort comprised patients older than 17 years, admitted from 2011 to 2018, and having the ICD-10 AM code for SCI. The dataset is a comprehensive record of a patient’s progression from the time of injury (usually ambulance), through the hospital stay, that is, the different care types up until discharge. The data included demographics, injury etiology, pathology, and radiology results, microbiology, medication, diagnosis, and discharge summaries (DS), and these were retrieved from one or more data sources.

We had a total of 1,382 patients in our dataset. The linking of patients across data sources varied, with around 80% of patients attributable across all internal data sources, and only around 40% present in external clinical registries (CR). Aside from the patient count, the number of records varied across sources, ranging from 15,397 (microbiology records) to 1,628,070 (medication records). The number of unique features (different types of tests/medication names/ICD codes, etc.) in the data warehouse alone was 5,593, thus resulting in a
Table 1 Sources for injury etiology

<table>
<thead>
<tr>
<th>Fields</th>
<th>Possible sources</th>
<th>Temporal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient_ID, DOB</td>
<td>Business Intelligence team</td>
<td>No</td>
</tr>
<tr>
<td>DOIJ</td>
<td>CR1, CR2, DS</td>
<td>No</td>
</tr>
<tr>
<td>Injury type (traumatic, nontraumatic)</td>
<td>CR1, CR2, DS</td>
<td>No</td>
</tr>
<tr>
<td>Injury cause</td>
<td>CR1, CR2, DS</td>
<td>Yes</td>
</tr>
<tr>
<td>Injury level (quadriplegia, paraplegia, etc.)</td>
<td>DS, ICD-10 AM coding</td>
<td>No</td>
</tr>
<tr>
<td>Neurology (C1–S5)</td>
<td>CR1, DS</td>
<td>Yes</td>
</tr>
<tr>
<td>ASIA (A-E)</td>
<td>CR1, DS</td>
<td>Yes</td>
</tr>
<tr>
<td>Catheter (permanent, intermittent, etc.)</td>
<td>DS</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Abbreviations: ASIA, The American Spinal Cord Injury Association (ASIA) impairment scale; CR, clinical registry; DOB, date of birth; DOIJ, date of injury; DS, discharge summary.

The results of completeness are shown in Fig. 1 (Supplementary Figure S2 for other data sources [available in the online version]). Date of injury (DOIJ) and American Spinal Cord Injury Association (ASIA) impairment scores are critical variables, and these have very low completeness in our dataset. DOIJ is required for temporal alignment of all variables and ASIA scores help assess the sensory and motor levels post-SCI injury.

The results of DQ evaluation are presented in Table 4 for the injury etiology data subset, with DQ failures annotated (in bold). Fields are identified as DQ failures if the percentage of values not meeting the criteria is in the majority, or Krippendorff’s $\alpha$ indicates poor agreement.

Our qualitative step of semistructured interviews to understand data provenance identified 11 subthemes and 3 main themes of data provenance that affect the DQ of our secondary use case (Supplementary Tables S3 and S4, available in the online version). The main themes were systems, processes, and actors.

Data Quality Constructs
The interview questions, identified provenance (listed below as “Interview takeaways”), and resolutions and for each of the DQ failures are enumerated below.
### Table 2: DQR for injury etiology

| Fields: patient ID, DOB, DOIJ, injury type (traumatic, nontraumatic), injury level (quadruplegia, paraplegia, etc.), injury cause, SCI ICD code |
| Temporal fields: ASIA impairment scale (A–E), neurology (C1–S5), bladder management (e.g., catheter type permanent, intermittent, and others) |

<table>
<thead>
<tr>
<th>Field</th>
<th>Complete</th>
<th>Correct</th>
<th>Current</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients</td>
<td>DQR 1: Pcount (all fields required to construct etiology are present)</td>
<td>DQR 3: Pcount (field values belong to allowed set)</td>
<td>DQR 13: Pcount (date time of the field is within the study duration and patient’s inpatient stay) Field ε [ASIA score, neurology, catheter]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DQR 4: Pcount (DOIJ, DOB format is correct)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>DQR 5: Pcount (unique (field) is true) Field ε [patient ID, DOIJ, injury type, injury level, injury cause]</td>
<td></td>
</tr>
<tr>
<td>Variables</td>
<td>DQR 2: Rcount(Fields have value)</td>
<td>DQR 6: α (DOIJ from 3 sources)</td>
<td>DQR 14: verifying DOB and DOIJ order Rcount(DOIJ &gt; DOB)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DQR 8: α (injury cause from 3 sources)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>DQR 9: α (neurology from 2 sources)</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>DQR 10: α (injury level from 2 sources)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>DQR 11: Rcount (neurology and injury level follows semantics)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>DQR 12: Rcount (field changes in value conforms to expert knowledge) Field ε [ASIA score, neurology, catheter]</td>
<td>DQR 15: recorded at admission and discharge Pcount (count(field) ≥ 2) Field ε [ASIA score]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>DQR 16: recorded over time Pcount(count(neurology, catheter) ≥ 1)</td>
</tr>
</tbody>
</table>

Abbreviations: ASIA, The American Spinal Cord Injury Association; CR, clinical registry; DOB, date of birth; DOIJ, date of injury; DQR, data quality rule; DS, discharge summary; ICD, International Classification of Disease; Pcount, patient count; Rcount, record count; SCI, spinal cord injury. Note: Krippendorff’s α.

### Table 3: Key interviewees in analyzing data provenance

<table>
<thead>
<tr>
<th>Data</th>
<th>Departments</th>
<th>Data sources</th>
<th>Roles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injury etiology</td>
<td>Spinal care team</td>
<td>Data registry 1 Data registry 2 Discharge summary</td>
<td>Clinician (1) Clinical research liaison officer (2)</td>
</tr>
<tr>
<td>Diagnosis (ICD coding)</td>
<td>Health information services</td>
<td>Data warehouse</td>
<td>Administrator (1)</td>
</tr>
<tr>
<td>Episode information</td>
<td>Business intelligence team</td>
<td>Data warehouse</td>
<td>Data custodians (3)</td>
</tr>
<tr>
<td>Pathology and radiology</td>
<td>Pathology and radiology team</td>
<td>Data warehouse, Radiology data silo</td>
<td>Pathologist (1) Radiologist (1) Laboratory technician (1)</td>
</tr>
<tr>
<td>Microbiology</td>
<td>Microbiology team</td>
<td>Microbiology data silo</td>
<td>Clinician (1) Laboratory technician (1)</td>
</tr>
<tr>
<td>Medication (stewardship and antibiotics)</td>
<td>Infectious diseases team</td>
<td>Data warehouse, Antibiotics dispensing management system</td>
<td>Clinician (1) Pharmacist (1)</td>
</tr>
</tbody>
</table>
Completeness failures manifest as missingness or incompleteness in the data, and such failures in our injury etiology dataset were identified through DQR1 and DQR2 in our assessment. The evaluation of DQ failures of injury etiology are described below.

Interview questions are as follows:

- How variables are recorded in the system?
- When are the injury etiology variables recorded?
- When is it not recorded?
- How is the ICD coding done for spinal injury?
- What is a typical spinal patient trajectory through the treatment workflow?

Interview takeaways: injury etiology lacked structured recording. The fragmented reporting of care specific information was available as scanned neurology charts, unstructured DS, or form notes when ordering of tests. Further, the hospital reports some of the fields to external registries (trauma and spinal registry databases). The data were retrieved from external sources and DS. Mapping the spinal patients to the external spinal registry database informed us of nonspinal patients in our cohort. This led to the investigation of why nonspinal patients were present in the cohort, requiring understanding of the provenance of ICD codes. Further, the treatment workflow of spinal patients helped us understand that the acute patients always get admitted to the acute ward in the spinal unit.

Resolutions: Fig. 2 shows our workflow for addressing completeness DQ failures of DOIJ and admit ASIA fields. Using the knowledge of treatment workflow, and leveraging data from external registries through data triangulation, we filtered out nonspinal patients from the cohort. After reconciling the data sources with high concordance, the DOIJ and admit ASIA still required manual extraction from the records. This achieved 52% completeness (Fig. 3). Finally, we removed cause as a required attribute as the injury etiology remained well defined without this attribute, and we were able to achieve 83% completeness.

Missingness were also identified in other datasets like medications and episodes. Interviewing the pharmacists revealed medication systems went electronic only in early...
2013. Thus, we were able to safely mark the entries as missing at random (MAR) and can prevent it from being a spurious signal of “medication not administered.” In the case of episodes data, missing variables of the episode dataset could be inferred through the understanding of the processes linked to generation of other variables, similar to our actions in the case of etiology data. For example, we were able to infer ICU admission and discharge times by checking the blood gas tests timestamps, as these tests are typically done early in the morning when the patient is in ICU. Similarly, standard normal ranges retrieved from the pathology department’s yearly audit logs complemented the test results by providing the missing metadata for normalizing test results.

Correctness
Correctness failures map to inconsistencies, coding, and concordance errors. We measured correctness across two distinct subdimensions as follows: (1) concordance for fields where we had values from multiple coders (DQR 6–10), and (2) correctness as plausibility validated by experts or common knowledge (DQR 3–5 and DQR 11–12). Of these, DQR 8...
to 10 identified concordance failures, and DQR 12 identified temporal plausibility failures. The evaluation of these failures and eventual resolution are described hereinafter.

Interview questions: questions for concordance (DQR 8–10)

- How are the injuries categorized?
- How was the coding of neurology done?
- Questions for plausibility (DQR 12)
- How in the system are the variables recorded?
- What is the process by which variables are measured and recorded?

Interview takeaways: clinical reevaluation of inconsistent records revealed complexities including nonstandardization of codes and coder interpretation that result in concordance failures. These may be interpretive in nature, for example, hematoma after a surgery could be interpreted as traumatic or nontraumatic, and push bike over ramp injury could be interpreted as sports or bike. In case of plausibility (DQR 12), the interviews highlighted the lack of first-class support for recording cohort-specific temporal progression for ASIA score, neurology, and catheter type fields.

Resolutions: after terminology standardization, the α score of injury causes improved to 0.85. Though this looked unreliable, both the sources were correct, factoring in the interpretive nature of categorization. During standardization, we cross pollinated the causes. For example, a “fall from bike,” categorized as a bike accident in one source and a fall accident in another, was updated to contain both causes in the record. For neurology, the data sources were the CR and DS. Low scores were due to the loss in temporality in the data recording in the DS, and due to coder bias. Further, DS as a source was considered unreliable due to lack of temporality and only ICD codes were used for recording of injury level. The CR was considered gold standard, and thus, the semantic mapping was updated between CR’s neurology and ICD injury level. DQ analysis of the progression of fields, such as ASIA scores, neurology, and catheter type, was precluded by the lack of any temporal metadata in the recording of these fields.

Different systems recording data in different forms cause terminology inconsistencies similar to those seen in the injury etiology dataset. These include radiology test names recorded as “X-ray chest” versus “chest,” in microbiology, “tracheostomy swab” versus “ear/nose/throat/eye culture.” Multipurpose medication is another such example. Propranolol (Apotex Pty. Ltd., Alphapharm Pty. Ltd., AstraZeneca Pty. Ltd.; New South Wales, Australia) is a dual use drug for suppressing blood pressure and heart rate, with suppressing heart rate being the primary reason, as it is prescribed to SCI patients. While standardized codes, such as Logical Observation Identifiers Names and Codes (LOINC) and Anatomical Therapeutic Chemical (ATC) help in baselining drugs to their generic names, encoding the contextual utility requires domain knowledge, and therefore understanding data provenance is integral to such secondary use.

Currency

Currency measures the quality of temporal information, and in our analysis of the injury etiology, currency measures are crucial for enabling the chronological reconstruction of a patient’s record. DQR 13, 15, and 16 reported poor DQ on the associated fields.

Interview Questions

1. What is the frequency of variables recorded?
2. When and where are the injury etiology variables recorded?

Interview takeaways: the system incorporated spinal specific information as scanned documents and in DS. Therefore, SCI-specific variables did not have first-class support of validation and metadata tagging such as timestamps. Temporal information of recording of ASIA scores and catheter information was unavailable.

Resolutions: scores recorded during admission were used as the lack of temporal recording made sequential alignment of the scores impossible. ASIA score and neurology at admission were used, and discharge ASIA score was discarded. The catheter field was discarded from the research dataset due to unavailability of temporal information, even though it is an important signal in analyzing infections.

Discussion

A methodical assessment of data provenance is enabled by our proposed systematic approach of identifying DQ failures through 3 × 3 DQA framework, and addressing these failures through identifying domain experts and conducting semi-structured interviews to understand the context of data generation. The questions were guided by the why, how, and who of data recording, to interpret the data in the context of its generation, and subsequent lifecycle. Data provenance has been highlighted as an important component of EHR secondary use, and other studies have documented the consideration of information flow as necessary for robust secondary use and avoiding biases.

Further, evaluating data provenance enables the reporting
of data characteristics in EHR centric studies through presenting data completeness, data collection and handling, and the types of data.36

The DQ failures identified in our data were of the typology well represented in the literature.13–20 Missingness is a common challenge in the secondary use of EHR, and its causes include data being digitized after start of study,14 and recording in free form clinical notes.16 Such missingness was identified in our study through understanding the systems through which data were recorded. The semistructured interviews with the actors recording it further clarified the unreliability of these values which led us to eliminate the fields altogether from our study. Data provenance is also essential to categorize observed missingness under the standardMAR, missing not at random, and missing completely at random categories, which Haneuse and Daniels57 formulated as “what data are observed and why.” We identified the categories of missingness through triangulation and understanding recording workflows, such as distinguishing between missing test values and tests not done, a crucial distinction as absence of test values is a valid signal by itself.59,60 Lack of system flexibility in recording specialized care group information or disease progression13,18,19,41 causes DQ failures. DQ failures increase as we traverse the data spectrum away from common, well-supported variables, such as pathology and radiology, and toward the variables of specialized care groups such as injury etiology in the SCI cohort. The data specific to specialized care groups are seldom appropriately represented in processes or systems,13,16,19 leading to workarounds such as unstructured recording and derivative extraction. A systematic approach to understanding data provenance is particularly necessary for such specialized care groups as the distinguishing features of the cohort are also the features with the least built-in quality scaffolding, and therefore need an investment toward DQ and provenance analysis prior to secondary use. The identification of valid sources for such data, context of the recording, and any associated implicit conventions requires domain expertise, and it is made possible through data provenance–focused semistructured interviews.

Secondary use of EHR needs to consider why a particular field was recorded, and if the recording intent is in alignment with, and sufficient for, the intended secondary use.20 In our initial data extraction, using ICD coding for spinal resulted in a dataset where 30% of the patients did not have spinal injuries and had been coded as spinal. This is specifically relevant in phenotype studies that build cohorts using ICD codes. Biased ICD coding can cause noncompatible patient records to be included in the dataset, and subsequent identification of such records is not feasible without a comprehensive understanding of data provenance as the “signature attributes” of the cohort could be naively interpreted as missing data points in such spurious records, masking the fact that these records do not belong in the cohort in the first place. Similarly, secondary use also needs to consider how a particular field was interpreted in clinical use, and what metadata were necessary to appropriately encode the field for secondary use. Pivovarov et al,42 for instance, have documented the importance of context in the secondary use of laboratory tests’ data and possibilities of bias due to lack of associated documentation. We observed such documentation bias in our test results data through lack of documentation metadata like normal ranges which skewed normalization of results, and were able to mitigate this through associating appropriate normal ranges to test results as identified through our provenance investigation.

Finally, the DQ failure analysis performed in this study spanned 6 months, largely a function of availability of domain experts. While this is not necessarily representative, it does emphasize the cost of such retrospective failure reconciliation, and motivates the need for better recording of metadata with a view toward eventual secondary use. The study also highlights the need for continuous collaboration with clinicians and domain experts during secondary use, such that the context associated with the data is incorporated into secondary use of the dataset.

Limitations
The nature of the research and the single-site focus of the study impose some limitations. Our study is based on the EHR of a specialized care group cohort, therefore the DQ failures and approaches to ascertain data provenance could be broader than what our dataset could illustrate. DQ failures and biases could also be introduced by the specifics of our study, such as the EHR systems, and institute specific workflows. A potential avenue of future research would be the comparison of the performance of models trained on such a DQ-validated data versus raw data.

Conclusion
The paper presents a systematic approach for the analysis of EHR DQ failures through understanding data provenance, and documents the resulting improvements in DQ for secondary use. Data provenance is investigated through semistructured interviews with domain experts, and the understanding of data provenance helps in reconciling DQ failures: evaluate if the issues can be fixed, mitigated, or if the records have to be discarded. Such reconciliation builds trust in the data for secondary use. Further, our semistructured interviews identified the three main themes of data provenance for secondary use of EHR data to be systems, processes, and actors.

Clinical Relevance Statement
Electronic health record (EHR data are reused for clinical research, quality assurance, and modeling among other secondary use cases and data quality assessment (DQA) is a critical step in determining its “fitness for use.” DQ failures revealed through the application of these frameworks should be followed-up with a contextual analysis that situates the data in the context of when, how, and who generated the data and therefore help in further evaluating its correctness, readiness for use, and trust in the data. The
The proposed approach enables such analysis, thereby allowing for the construction of robust datasets for secondary use.

**Protection of Human and Animal Subjects**

The study was performed in compliance with the Austin Health Human Research Ethics Committee Ethical Approval (HREC). Ethics approval obtained from Austin on August 18, 2017, reference no LNR/17/Austin/408.

**Authors’ Contributions**

N.A.: Study design, data collection and formatting, analyses and evaluation, interviews, manuscript preparation, tables, and figures. W.B.: Study design, intellectual input on statistical analyses and modeling, manuscript preparation, and review. A.N.: Study design, interviews, clinical interpretation and validation of results, manuscript preparation, and review.

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**Conflict of Interest**

None declared.

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