Electronic Health Information Quality Challenges and Interventions to Improve Public Health Surveillance Data and Practice

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ABSTRACT

Objective. We examined completeness, an attribute of data quality, in the context of electronic laboratory reporting (ELR) of notifiable disease information to public health agencies.

Methods. We extracted more than seven million ELR messages from multiple clinical information systems in two states. We calculated and compared the completeness of various data fields within the messages that were identified to be important to public health reporting processes. We compared unaltered, original messages from source systems with similar messages from another state as well as messages enriched by a health information exchange (HIE). Our analysis focused on calculating completeness (i.e., the number of nonmissing values) for fields deemed important for inclusion in notifiable disease case reports.

Results. The completeness of data fields for laboratory transactions varied across clinical information systems and jurisdictions. Fields identifying the patient and test results were usually complete (97%–100%). Fields containing patient demographics, patient contact information, and provider contact information were suboptimal (6%–89%). Transactions enhanced by the HIE were found to be more complete (increases ranged from 2% to 25%) than the original messages.

Conclusion. ELR data from clinical information systems can be of suboptimal quality. Public health monitoring of data sources and augmentation of ELR message content using HIE services can improve data quality.

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Electronic laboratory reporting (ELR), the electronic submission of laboratory data following the confirmation of an infectious disease, was demonstrated more than a decade ago to be an effective method to increase the timeliness of notifiable (communicable) disease reporting as well as the number of notifiable disease case reports submitted to public health agencies.[1] With pervasive, increasingly sophisticated information technology and the rise of interconnected systems, the medical community recognizes the need for proven methods and best practices for managing electronic health information. This recognition has led to investments from the U.S. government, states, and a number of private foundations totaling billions of dollars for the development, implementation, and adoption of electronic health record (EHR) systems, which support laboratory, surveillance, and other information systems.[2–6] Such initiatives seek to improve the timeliness, accuracy, and completeness of data needed to support a variety of services, including surveillance activities.

The number of state health agencies receiving ELR data has increased during the past decade. Currently, more than 40 states in the U.S. have the capacity to receive electronic reports from laboratories,[7] and the number of electronic reports submitted to state agencies is expected to increase given Stage 2 "meaningful use" program incentives (i.e., increased reimbursement for the adoption and use of EHR systems) from the U.S. Centers for Medicare & Medicaid Services that require eligible hospitals and encourage eligible providers to submit notifiable disease laboratory results to public health agencies using ELR.[8]

Simply reporting laboratory data electronically instead of using paper, however, does not solve the fundamental challenge of receiving high-quality, reliable data in support of public health functions. Several studies suggest that ELR may not improve data completeness.[9–11] These studies indicate that important challenges persist beyond adoption of ELR for the public health surveillance and informatics communities to collaboratively address. One of those challenges is improving poor data quality.

Poor data quality is a pervasive issue affecting all industries and organizations using information systems.[12] Typical data quality issues encountered include inaccurate data, inconsistencies across data sources, and incomplete (or unavailable) data necessary for operations or decisions.[13] In health care, the completeness of data in EHR systems has been found to vary from 30.7% to 100.0%.[14]

Despite the pervasive nature of this problem, there is little evidence characterizing the impact of poor data quality on health-care delivery processes or population outcomes. General estimates of impacts include increased costs, with up to 40%–60% of a service organization's expenses consumed as a result of poor data; poorer decisions that take longer to make; lower consumer satisfaction with information systems; and increased difficulty in reengineering work and information flows to improve service delivery.[13] Impacts on health care include less informed decisions when humans or machines use poor quality data inputs from EHR systems.[15,16] For example, a study comparing electronic pharmacy data with the medications actually taken by patients found that only 5% of patients had perfect agreement between their computerized medication profile and the medications actually consumed.[17] Clinical queries of such pharmacy databases could lead to errors of omission and comission when making prescribing decisions.

The importance of data quality is increasing as the nation develops an infrastructure to collect, store, manage, and exchange large amounts of health-care information. Policies that are encouraging ELR, including the Health Information Technology for Economic and Clinical Health (HITECH) Act provisions of the American Recovery and Reinvestment Act of 2009, also incentivize hospitals and physician practices to use technology to better coordinate patient care as well as the information about care delivery processes.[18,19] Better management and coordination of information across the nation's fragmented health delivery system require health information exchange (HIE), which is defined as the electronic transfer of clinical and administrative information across diverse and often competing health-care organizations.[20,21]

Federal policies and programs to encourage HIE have given rise to a number of HIE organizations in nearly every state and territory.[22] These organizations primarily focus on improving individual patient care processes and outcomes by leveraging large volumes of clinical and administrative data from payers, hospitals, outpatient clinics, and pharmacies. In addition to patient care, several HIEs are supporting population health functions, including ELR to public health agencies.[23–26] Because HIEs are patient-centric, they have the capacity to provide public health programs with comprehensive medical records. In the case of ELR, an HIE may be able to deliver liver enzymes in parallel with the results of a positive laboratory test for hepatitis C. Yet, little evidence remains demonstrating how and to what effect such enhanced ELR would have on public health surveillance programs.

Given a paucity of evidence that ELR does or does not impact the quality of data received by public health, we examined the completeness of ELR data from

clinical information systems in two states. In addition to characterizing the completeness of ELR data, we further compared raw data directly sent from clinical information systems with data enhanced by an HIE. If an HIE can improve the completeness of ELR data submitted to public health, enhancement methods would represent a valuable, effective method for improving notifiable disease data quality. Improving data quality will likely translate into improvements in disease surveillance processes, impacting both clinicians and public health professionals.

METHODS

The scope of our research included the following aims: (*1*) measuring the completeness of ELR data received from clinical information systems, (*2*) comparing data from Indiana-based information systems with comparable systems in another state (Wisconsin), and (*3*) comparing the completeness of "raw" data (e.g., unaltered, unedited ELR messages) with "enhanced" data (e.g., ELR messages with corrected syntax and test names mapped to standard vocabularies) from an HIE.

This study focused on data completeness. Completeness in the context of surveillance refers to both the proportion of diagnosed cases reported to public health and the proportion of fields in a case report completed by the submitting hospital or laboratory.[27] As previously described, ELR messages' ability to increase the proportion of diagnosed cases reported to public health has been well established.[1,9,28] Therefore, we concentrated the study on measuring the completeness of the data within ELR messages transmitted by a data source (e.g., hospital, laboratory, or HIE).

To measure the completeness of laboratory data, we identified a minimum dataset for ELR messages that would meet the information needs of public health agencies that receive the data. The minimum dataset was drawn from public health law and practice, and it has been fully defined and described previously.[23] We calculated completeness of each field in the minimum dataset by dividing the number of values (non-null) present in a data field by the total number of possible values for that field. We multiplied the resulting proportion by 100 to derive a percentage. We also calculated the difference between percent completeness across samples.

The study data originated from production information systems deployed in a variety of clinical and public health settings. The first sample contained raw messages received from 54 distinct hospital and laboratory information system interfaces during a one-month period (November 14 to December 15, 2010) by the Indiana Network for Patient Care (INPC), an operational HIE[29,30] that includes hospitals, reference laboratories, and the state health laboratory. Only messages that contained the results for 68 potentially reportable condition tests (defined by Indiana Administrative Code 410-1),[31] whether positive, negative, or inconclusive, were included in the analysis.

The second sample contained randomly selected raw messages received from 13 distinct hospital and laboratory information system interfaces during a multiyear period (May 3, 2007, to November 18, 2010) by the Wisconsin State Laboratory of Hygiene, the coordinating agency for ELR for the Wisconsin Electronic Disease Surveillance System (WEDSS). WEDSS was developed and is maintained by Atlas Public Health, a division of Atlas Development Corporation, through a contractual arrangement with the Wisconsin Department of Health Services (WDHS). Random sampling during multiple years was necessary to generate a representative sample of ELR messages comparable to the sets from Indiana that would meet the requirements of the WDHS ethics board. The reportable conditions selected from WDHS were defined by Wisconsin law, although our analysis found that the two states have extremely similar condition sets.

The third and final sample contained enhanced messages representing 49 distinct hospital and laboratory sources processed by the INPC during the same one-month period as the first sample (November 14 to December 15, 2010). These messages were extracted from the outbound message queue, which contains only reportable messages bound for the state health agency. The INPC uses the Regenstrief Notifiable Condition Detector (NCD)[32] to critically examine all ELR messages from INPC interfaces that potentially contain notifiable disease results. Messages determined to definitively contain reportable results are sent from the outbound queue to the state health agency on behalf of the INPC's member institutions. The NCD eliminates rule-out tests and other results that, upon inspection, are found to not be reportable under Indiana state law. Therefore, this set represents principally ELR messages from the raw sample that were confirmed by the NCD to be reportable under law.

The NCD further enhances ELR messages through translation and augmentation methods. For example, local laboratory codes are mapped to equivalent Logical Observation Identifiers Names and Codes (LOINC®). The LOINC are appended to the original messages prior to transmission to the state health agency. The NCD further examines incoming messages for provider information (e.g., National Provider Identifier, address of the hospital or practice, or phone number for the

department or clinic) and attempts to add any missing provider information found in a table of providers stored in the INPC. Furthermore, laboratories may improperly place data such as units of measure in a comment section of the ELR message, so the NCD also makes syntactical corrections to messages.

RESULTS

Measurement and comparison of ELR data completeness from two states

We measured and compared samples of ELR messages from two states, Indiana and Wisconsin. The first sample (from Indiana) contained 249,528 messages from the INPC's raw queue for incoming messages. The second sample (from Wisconsin) contained ELR messages sent from laboratory systems to the WDHS. This sample contained 222,335 messages.

Table 1 summarizes and compares the calculated completeness for each field in the two samples. Completeness varied widely across both samples, ranging from 5.7% to 100.0% in the Indiana sample and from 14.4% to 100.0% in the Wisconsin sample. Six of the 18 fields in the Indiana sample were <50% complete, while four fields in the Wisconsin sample were <50% complete.

Measurement and comparison of ELR data completeness within an HIE

Next, we compared the first sample (the raw messages from Indiana) with a third sample (enhanced messages) of reportable results from the Regenstrief NCD post-processed queue. This sample contained 16,365 messages.

Table 2 summarizes and compares the calculated completeness for each field in the two samples. Completeness again varied between the two samples. The variation in completeness in the enhanced sample was less than in the raw sample, ranging from 18.3% to 100.0%. Of the 18 fields, 11 were observed to be

Table 1. Comparison of data completeness for ELR messages sent in Indiana (November 14–December 15, 2010) and Wisconsin (May 3, 2007, to November 18, 2010) to state public health departments

Key data element	*Corresponding HL7 field*	*Percent complete: Indiana*	*Percent complete: Wisconsin*	*Difference*
Patient identifier	Patient identifier (PID-3)	100.0	99.9	–0.1
Patient name	Patient name (PID-5)	100.0	99.8	–0.2
Patient date of birth	Date of birth (PID-7)	99.8	98.5	–1.3
Sex (gender)	Administrative sex (PID-8)	99.9	98.3	–1.6
Race	Race (PID-10)	44.9	61.4	+17.5
Patient address	Patient address (PID-11)	55.5	89.6	+34.1
Patient home phone number	Phone number (PID-13)	47.2	35.4	–12.2
Ethnicity	Ethnic group (PID-22)	6.3	14.4	+8.1
Name of attending physician, hospital, clinic, or submitter	Ordering provider (OBR-16)	95.2	90.6	–4.6
Telephone number of attending physician, hospital, clinic, or submitter	Callback number (OBR-17), staff phone (STF-10)	NA	92.0	NA
Address of attending physician, hospital, clinic, or submitter	Staff office/home address (STF-11)	NA	99.1	NA
Test name	Observation identifier (OBX-3)	100.0	99.4	–0.6
Test results or laboratory interpretation of test results	Observation value (OBX-5)	97.2	100.0	+2.8
Specimen source	Specimen source (OBR-15)	68.4	100.0	+31.4
Units of measure	Units (OBX-6)	5.7	41.6	+35.9
Normal range	Reference range (OBX-7)	8.3	19.0	+10.7
Abnormal flag	Abnormal flags (OBX-8)	23.0	66.4	+43.4
Status of test result	Observation result status (OBX-11)	97.0	99.5	+2.5

ELR = electronic laboratory reporting

HL7 = Health Level 7

PID = patient identification

OBR = observation request

STF = staff

NA = no applicable

OBX = observation segment

Table 2. Comparison of data completeness for ELR messages received from providers and enhanced by an HIE prior to transmission to a state public health department in Indiana: November 14–December 15, 2010

Key data element	*Corresponding HL7 field*	*Percent complete raw data*	*Percent complete enhanced data*	*Difference*
Patient identifier	Patient identifier (PID-3)	100.0	100.0	None
Patient name	Patient name (PID-5)	100.0	100.0	None
Patient date of birth	Date of birth (PID-7)	99.8	99.8	None
Sex (gender)	Administrative sex (PID-8)	99.9	99.9	None
Race	Race (PID-10)	44.9	60.3	+16.4
Patient address	Patient address (PID-11)	55.5	63.3	+7.8
Patient home phone number	Phone number (PID-13)	47.2	72.8	+25.6
Ethnicity	Ethnic group (PID-22)	6.3	18.3	+12.0
Name of attending physician, hospital, clinic, or submitter	Ordering provider (OBR-16)	95.2	96.5	+1.3
Telephone number of attending physician, hospital, clinic, or submitter	Callback number (OBR-17), staff phone (STF-10)	NA	74.1	NA
Address of attending physician, hospital, clinic, or submitter	Staff office/home address (STF-11)	NA	85.6	NA
Test name	Observation identifier (OBX-3)	100.0	100.0	+0.7
Test results or laboratory interpretation of test results	Observation value (OBX-5)	97.2	98.9	+1.7
Specimen source	Specimen source (OBR-15)	68.4	49.3	–19.1
Units of measure	Units (OBX-6)	5.7	20.0	+14.3
Normal range	Reference range (OBX-7)	8.3	21.0	+12.7
Abnormal flag	Abnormal flags (OBX-8)	23.0	32.5	+9.5
Status of test result	Observation result status (OBX-11)	97.0	99.4	+2.4

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more complete in the enhanced sample. Four of the fields in the enhanced sample were <50% complete.

DISCUSSION

To effectively perform surveillance as well as other core functions, public health agencies require access to "timely, accurate, and complete data."[33] The results of this study confirm that laboratory data from clinical information systems vary in their completeness. In many cases, data important to surveillance processes are missing, indicating suboptimal ELR data quality. This study further demonstrates that HIEs can employ methods that mitigate ELR data deficiencies, improving the completeness of health data electronically transmitted to public health.

This study primarily quantified what many in public health are likely to encounter in daily work: clinical data are heterogeneous in completeness across and within information systems and jurisdictions. Some laboratory information systems routinely transmit the provider's phone number, while others almost never provide this data element. Understanding the magnitude of the problem is necessary to develop strategies to mitigate the issue. Consequently, while such tacit knowledge is not novel, it is rarely measured and disseminated. Furthermore, state or regional differences are almost never compared or examined.

The heterogeneity of data has implications for public health policy and practice. Unfortunately, many public health officials, like data consumers in other health-care segments and industries, may simply presume that data are easily and uniformly captured and stored across the spectrum of health-care services. In reality, data are captured for a specific purpose, and collecting additional data elements is costly. Additional data

elements require staff to ask for and then record the information, which translates into additional time and labor. Therefore, data consumers must understand the impact of the cost of data collection on the characteristics of data captured in various environments (e.g., their completeness) when making decisions about secondary use. Epidemiologists, for example, might benefit from understanding that elements such as the provider's phone number and address are poorly populated by laboratory information systems. In Indiana, very few laboratories provided these values because clinical information systems rarely communicate these details to the laboratory system when ordering a test. In Wisconsin, these values were observed to be the mailing address and main phone number for the hospital or clinic; therefore, while populated, the value of the field might not be useful to a communicable disease nurse attempting to call the ordering physician. Although these fields are required according to state (e.g., Indiana Administrative Code 410) or federal (e.g., meaningful use) regulations, it does not guarantee that they will be complete and available for public health surveillance processes. Thus, policies requiring additional data elements are unlikely to impact data-collection processes unless laboratories and hospitals are incentivized to capture the additional data elements needed for public health surveillance processes.

For several fields, the difference in completeness between the Indiana and Wisconsin samples was striking. This variance can be explained, in part, by examining the data source and the level of control exerted by public health (data not shown). The Wisconsin sample came from 13 sources, with the majority (slightly >65%) of the data originating from a source laboratory operated by the state health department. The Indiana samples originated from 49 sources, of which only two were operated by a public health agency representing just 0.85% of ELR message volume. When public health operates the laboratory, the agency has greater control over the breadth and depth of data elements exchanged between the laboratory and the disease surveillance program that receives the ELR messages. For example, if specimen source is needed for surveillance programs, and the health department administratively and financially manages the laboratory, then the agency can more effectively specify the format and data content of the electronic message sent to disease surveillance systems.

Although public health agencies do not have direct control over hospital and referral laboratory data, agencies can establish guidelines or requirements for ELR messages and work with data sources to meet the established standards. The Wisconsin and Indiana health departments provide guidance to hospitals and laboratories on the necessary data elements and formatting of the ELR messages. Both states also monitor incoming data through periodic audits, notifying data senders when certain fields are missing. Despite their best efforts, however, hospitals and laboratories continue to send incomplete data. As the use of electronic methods for submitting notifiable disease information increases given the provider incentives to achieve meaningful use, strategies for prioritizing data elements and cooperatively working with hospitals and laboratories will be critical to ensuring accurate, timely, and complete surveillance data. Public health agencies will further need access to resources and tools to support their monitoring of data completeness, and there will need to be incentives for hospitals and laboratories to make changes to their systems and processes of capturing data that are important for surveillance.

Comparing the raw Indiana ELR messages with enhanced messages demonstrates that HIE infrastructures such as the INPC can improve data completeness. The completeness of all but one field in the enhanced sample was superior to the equivalent fields in the raw sample. The improvements in completeness for provider addresses and phone numbers were a direct result of HIE processes designed to enhance provider information. The INPC identifies all providers present anywhere in the message and resolves their identities using its Master Provider Index. The index possesses data elements such as the provider's name, clinic address, phone number, role (e.g., physician or physician assistant), and staff identification number. Using its Master Provider Index, the INPC is able to dramatically increase the amount of provider detail for the messages sent to the state health agency.

While most fields in the enhanced messages had higher data completeness, one field (specimen source) was less complete than in the raw sample. The principle reason for this lack of completeness was that a higher proportion of the enhanced sample included microbiological and susceptibility cultures. Cultures are typically not reported with a specimen source, especially in repeating ELR message segments that contain all of the various microorganisms tested for in the culture. Furthermore, some data sources report micro results wholly in the comment section of a message rather than the standard results field. The use of repeating segments and nonstandardized sections makes micro and susceptibility cultures difficult to process. Future analyses of completeness will adjust for the result type to prevent overrepresentativeness of micro and susceptibility messages. Moreover, better use of special segments referred to as abnormal flags would improve

the ability of Regenstrief NCD's and other clinical information systems to identify and route notifiable cases to clinicians and public health agencies.

Finally, incomplete data affect public health practice. Effective surveillance of disease outbreak and appropriate case investigation procedures are hindered when certain data elements are missing in more than half of the cases. For example, data on race were absent more than one-third of the time in the Wisconsin and Indiana samples and data on ethnicity were present less than one-fifth of the time. However, public health agencies are charged with monitoring disparities in health-care access and disease burden. Consequently, statistics on minority disease burden using only ELR data would likely underestimate the true disease burden for some patient populations.

Another challenge confronts infection preventionists who are charged with reporting notifiable disease cases to public health agencies. The poor rate of usage of the abnormal flag (i.e., a special indicator that the laboratory test result is outside of its normal range or a microbiology culture is susceptible) makes it difficult to deploy technologies such as the NCD that could support infection-control practice by reducing the need for infection preventionists to manually identify notifiable results. In both cases, downstream public health processes are impacted by the inability of clinical information systems to produce complete ELR messages.

Limitations

This study was subject to several limitations. One limitation was that the impacts upon public health surveillance processes were only estimated. While the literature provides some evidence on the impact of poor data quality, we did not measure the specific impact of missing data in surveillance processes. Furthermore, measurable improvements to clinical and public health workflows as a result of data enhancements were not captured in this study. Future work should use observational methods to assess the impact of HIE and ELR interventions on work and information flows.

Furthermore, the INPC and WDHS are both early adopters of ELR. The INPC has partnered with local and state health agencies numerous times for more than a decade to improve public health reporting, and the INPC has invested heavily in the development and maintenance of its infrastructure. Similarly, WDHS has partnered with its state and regional laboratory providers for more than a decade to improve reporting in its state. Therefore, the results of studies in these states may not be generalizable to all state health departments.

CONCLUSIONS

Poor quality data exist in clinical information systems and present a challenge for public health agencies that increasingly look to EHR systems for data to support their work processes. For public health reporting, many data elements necessary to support surveillance processes are missing. Public health agencies can use policy to indirectly affect sending facilities ELR messages, although the effectiveness of these policies is likely limited. Methods employed by HIEs to improve data quality, including standardization of clinical vocabularies and enhancing ELR messages with missing demographic data for patients and providers,[23,34] can augment public health policies to improve completeness, supporting local needs to investigate disease outbreaks as well as federal goals to create meaningful use of EHR systems.

Despite current data quality challenges, it is possible to build an information infrastructure that is capable of supporting a wide range of uses of electronic clinical data in public health. The construction of the infrastructure will take time, resources, and energy from both surveillance and informatics professionals and will require partnerships with clinical organizations to change information systems and processes.

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