

# alt.metadata.health: Ontological Context for Data Use and Integration

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**Abstract.** Increasingly powerful computers and increased emphasis on evidence based decision making are creating a demand for merging and integrating data from different sources into a single data set. The demand for data is outstripping our ability to ensure data integrity, and sometimes analysis is performed on data that are not appropriate for the purposes they are used for. Here we describe problems that arise when data from different sources are merged, and we suggest that one way to add context to data so that users can make informed decisions about their ontological context is through ontology-based metadata. Examples of the problem are taken from health data with emphasis on difficulties in standardizing Emergency Room wait times. We describe eight fields that can be used to capture contextual metadata. These fields are captured using ethnographic methods from users and database stewards who frequently understand precisely how context and institutional usage have shaped interpretation of semantic fields. We argue that attaching a portable archive of ontological context to travel with data—based on information from users and developers—is a means of ensuring that data are integrated and compared in multiple contexts with greater integrity and more robust results.

**Key words:** data integration, data quality, health informatics, indicators, ontology, semantic interoperability

## 1. Introducing complexity: data and representation

Data are the basis for information generation and knowledge creation. They carry, however, an authority that frequently supercedes their quality. Many informatics-supported decisions are based on data of questionable quality (Longley et al. 2001; Balka 2004). A commensurate and perhaps more insidious problem is the use of data that are simply not suitable for the analysis at hand (Schuurman 2004b). Relevance is one of the key issues that emerges as more and more data are secondary (i.e. data were collected for one purpose and used for another). Data are after all representations of the world not the world itself; they carry with them political assumptions and agenda that are invisible to users (Woods 1992; Bowker and Star 2000).

As Schmidt and Bannon (1992) have pointed out, material representations of information exist as objective phenomenon and can be manipulated as an artifact, but the semantics of the information carried by the artifact “exist ‘in the mind’ of the beholder and the acquisition of information conveyed by the artefacts requires an interpretive activity on the part of the recipient.” They suggest (p. 27) that “cooperative work is not facilitated simply by the provision of a shared database, but requires the active construction by the participants of a common information space where the meanings of the shared objects are debated and resolved” and that “objects must thus be interpreted and assigned meaning.” Common information spaces must be negotiated and established by all involved actors (Schmidt and Bannon 1992). As Gerson (1989) has pointed out, there are multiple actors, each with differing perspectives (which may be incommensurate), and the points where they come together may represent only a small subset of activities of each (Schmidt and Bannon 1992). Gerson suggests that we need models that represent multiple information spaces, that are concerned with the specifics of cooperation among actors, “who don’t necessarily agree on anything, or whose cooperation is strictly bounded in time, location, and scope” (Gerson 1989, personal communication, cited in Schmidt and Bannon 1992, p. 40).

Although Gerson identified a need nearly 20 years ago for models that represent multiple information spaces and can reflect the dynamic nature of cooperation, data issues related to optimal scientific collaboration remain a key topic in computer supported cooperative work. To date, there is no systematic means of imbuing data with context in order to determine relevance for the task at hand. Indeed data are usually considered appropriate by virtue of their existence (Schuurman 2004a). Emergency room wait times are, for instance, bandied about as fact by hospital administrators and the media. In reality, they are compiled differently across jurisdictions and are difficult to compare. This type of problem can be thought of as a problem associated with large scale distributed computer-supported cooperative work, which increasingly involves analysis of data across multiple organizations and computing platforms.

In recent years, as computing systems have become more advanced and emphasis on evidence based decision making in medicine as well as evidence based policy—especially in public health—(Balka 2003a, b) has increased, problems with data have increased. Tools for generating maps have become more accessible, and interest in mapping information graphically with the use of geographic information systems has grown, while interest in the robustness and reliability of data has stagnated. In effect, use of data analysis has far out-stripped ability to assess data and determine to what extent data are suitable for particular types of analysis. Similarly, although limitations related to the use of linked health data from multiple sources have been recognized (Reid et al. 2004), the desire to increase the evidentiary basis of decision making in health care (Armstrong et al. 2001; Stein 2001; Timmermans and Berg 2003; Wiener 2000) has served as a catalyst for the use of such linked data, in spite of its limitations.

At the same time that policy makers have sought sophisticated analyses and representations of data (including, for example, maps showing the incidence of disease in a geographic region, or comparisons of waiting times in emergency rooms in different hospitals), researchers have struggled with the limitations inherent to datasets. A small sub-set of researchers has worked to overcome those limitations in scientifically sound ways with emphasis on semantics, data standards, and interoperability (Bishr et al. 1999; Harvey et al. 1999; Brodaric and Hastings 2002; Fonseca et al. 2002; Harvey 2003). Each of these issues bears on the problem of integrating data from different sources into a single data set for purposes of analysis. What is needed is a way to dimensionalize data so that users can make informed decisions about their ontological context.

Schuurman and Leszczynski (2006) have identified context-based metadata as one promising approach for resolution of epistemological issues that are increasingly emerging with the use of data from multiple sources to address complex issues. Ontology-based metadata are envisaged as a means of dimensionalizing metadata (data about data) to include ontological information about context, rationale for initial data collection, and a context for future usage. As Schmidt and Bannon (1992) pointed out, tasks as seemingly simple as identifying the context of information or the originator of information necessitate numerous decisions (should the representation of the originator of the information be textual, or pictorial, or by position? Which properties are pertinent in which situations?) and have implications for designing computer supported cooperative work systems. Developing context or ontology-based metadata also extends the Science and Technology Studies (STS) project by enlisting ethnographic techniques not to *study* existing technologies, but to participate in their construction. They are a means of collecting and using qualitative data to enrich extant data by providing ontological context to semantic terms used to describe attributes. Such use-context information becomes part of an extended metadata format that is compatible with ISO 19115 standards for communicating metadata for the purposes of data interoperability. The advantage of embedding ontological context in metadata is that it is an existing and established vehicle for attaching data about data. There are already mandates in place for metadata (e.g. ISO 19115). Alt.metadata is a means of taking advantage of this requirement to provide skeletal information beyond address and date of collection. This innovation seeks to balance qualitative enhancement of data with attendant attention to idiographic details and the need for data in informatics.

In this paper, we begin by describing the problems inherent in semantic interoperability. We draw on insights from social studies of science and technology, ethnographic approaches to computer system design and geographic information science (GIS) to illustrate some of the difficulties that arise when data are integrated from multiple sources. A detailed example of the difficulties of interpreting and integrating data from multiple sources with respect to hospital emergency room waiting times is used to illustrate our points. We then describe

how context-based metadata might contribute to more nuanced metadata, and act as the basis for informed decision making about use and robustness of data integration from multiple sources. A framework for the collection of context-based metadata is described, and examples of what the resultant metadata might look like are provided. In addition, we outline the ethnographic processes necessary to collect extended metadata.

## **2. Semantic data interoperability and the vagaries of language**

Semantic data interoperability entails the use of data collected and designed for a specific purpose in different contexts. Using data from multiple sources for analysis of any phenomena entails the presumption that the data are appropriate and comparable. This is, however, seldom the case. Gambling, for instance, is linked to higher rates of gambling-related suicide. In Alberta in 2003, there were 140 suicides linked to gambling debts. In Ontario in 2003, there were 15 deaths classified as suicides that were linked to gambling (CBC News, November 4, 2004). Ontario's population is greater than Alberta's and presumably there are proportionally more gambling venues. Should one conclude that gambling is more profitable in Ontario than Alberta and thus leads to fewer cases of depression linked to debt? The more likely scenario is that the criteria for linking suicides to gambling are more stringent in Ontario than Alberta. A similar problem occurs with birth weight which is defined differently in different jurisdictions. When data are collected via computer, additional semantic complexity may be introduced.

Computer systems often require users to enter values into fields (such as the time a patient arrives in an emergency room, or the time the patient is seen by a physician). To the extent that each manufacturers' emergency room computer system varies, the specifics of the data collected may vary (e.g., one system may request time of arrival in an ER, another may request time seen by a triage nurse, etc.). However, both fields may be called arrival time. In each instance the semantic content of the database is superficially comparable but a closer look reveals critical differences. The trouble with semantics is that they are used differently by different communities of discourse—a phenomenon that Robinson and Bannon have called ontological drift—a shift in meaning which can occur when artefacts move between semantic communities. In some contexts in which language is used there may be few consequences associated with differences in intended meaning associated with a term, while in other settings—such as those we describe here—the consequences can indeed be great.

Semantics are in effect “boundary objects” that serve as emissaries between different use-context communities. First introduced by Star and Griesemer (1989), boundary objects are a talking about and comparing nearly-but-not-equivalent scientific objects among different disciplines and sub-disciplines. Boundary objects are “standardized packages” or grey boxes that are adopted by

members of different social/scientific domains to temporarily stabilize a definition (Fujimura 1992; Harvey and Chrisman 1998; Chrisman 1999). In effect, they are unconscious compromises about what something really means—which support work between different use-context situations. In the case of data, boundary objects are called the same thing (e.g. suicides linked to gambling or babies with low birth weight or emergency room wait times) but they mean different things in their respective communities, or they reflect different meanings depending on the context in which data were collected. The result is, however, always that their use differs from community to community (e.g., ER wait times might be used by patients to push for more services, by staff to pursue improved staffing, or by management to argue for improved non-emergency services). Boundary objects allow for superficial agreement whilst permitting different uses and agenda with respect to scientific objects.

Decisions for merging data are, however, based on the superficial meaning of such terms in the absence of contextual information. Such interoperability decisions are frequently justified on the basis of the potential that merged data sets hold for decision making. These types of data integration decisions are based on a set of core assumptions (e.g., that semantic variability of data does not exist) that are seldom met.

Even the most banal of concepts such as “urban” and “rural” have different meanings in different contexts. Merging two datasets based on the assumption that their terms are similarly defined leads to error in the data. “Range” can refer to scope; the habitat of animal; a stove top used for cooking; a spread of values; a series of mountains in a line; a place where shooting is practiced; and a verb meaning “to roam”. As linguists have argued (e.g. Wooton 1975), language makes sense within specific contexts. If we are talking about cooking, then we will likely interpret “range” as part of a cooker. This sense making is frequently contextual. Indeed words often require context to be understood. Yet, databases seldom include detailed meaning about attributes nor their intended use. Even when attribute interpretation seems self-evident, semantic interpretation varies widely.

In British Columbia, several government ministries have separately collected and maintained environmental and forest resource data sets. These describe the same geographical entities using different schematics and semantics. Common procedures exist for feature code identification, digitizing thresholds, and naming conventions in the province. There remains considerable heterogeneity between schematics and semantics to the extent that even roads are differently defined among different ministries (Schuurman 2002). Similar problems of semantic interoperability exist in other datasets. For example, in the Vancouver region of British Columbia, air quality is reported for different point locations at intervals throughout each day. The air quality is expressed as an index value and the values are associated with a scale in which good quality air is below 20 on the scale. One might assume that the values are calculated based on comparable factors, but a closer look at the breakdown of the air quality index for each monitoring station

reveals that many of them are calculated differently (Schuurman 2005). Values that are similar for two locations are frequently based on the measurement of different pollutants. The calculation for Abbotsford is based on CO, SO<sub>2</sub>, PM<sub>10</sub> and OZ. The index value for Burnaby Mountain (where Simon Fraser University is located) is based on OZ and NO<sub>2</sub>. Clearly these are not strictly comparable values.

The difficulty of semantic interoperability increases with the level of abstraction associated with a given term so that the more complex a set of concepts articulated through data, the harder it is to use them with other data. For example, measuring the concept “continuity of care” (“the extent to which health care services over time are perceived as a coherent and connected succession of events consistent with a patient’s medical needs and personal context”... “belies the historical difficulty of defining, measuring and valuing continuity across different types of health care”. Reid et al. (2004) argue that the core notion of continuity is that patients experience their care as connected and coherent over time. Three main types of continuity support this “uninterrupted succession of events:” informational, management, and relational continuity.<sup>1</sup> To confuse matters more, relational continuity (one of the defining attributes of primary care) is at times referred to as longitudinality (Reid et al. 2004 p. 2). Several types of data exist that can be used to generate measures of continuity of care, including administrative data, patient self-report data, collected either locally (e.g., as part of a local study), or as part of a larger data set (e.g., as part of the National Population Health Survey) (Reid et al., p. 4). At any given time, the term “continuity of care” could be used to refer to any one or more of the dimensions outlined above, and any one of the data sources (e.g., administrative data, self-report data) that may be used to assess continuity of care. When multiple attributes are combined into indices, the instability of language is compounded. As Reid et al. (p. 4) point out, “over the last 30 years, a variety of tools, geared to administrative data, have been developed to measure a patient’s propensity to visit the same provider.” These include the ‘usual provider continuity’ index (UPC), the ‘continuity of care’ index (COC), the ‘known provider continuity’ index (K), the ‘likelihood of continuity index (LICON), the sequence of continuity’ index (SECON), the ‘likelihood of sequential continuity’ index (LISECON)” among others. Yet any or all of these—each of which has theoretical strengths and weaknesses, could be used to mean “continuity of care” (Reid et al. 2004).

Phenomena that are in early stages of study—for example, adverse events related to medical technology, or health literacy—present a related semantic challenge. The meaning of terms such as technology related adverse event or health literacy have often not reached semantic stability within a single context, much less across contexts, although there may be a number of reasons to measure such phenomena. Often such semantic instability may be indicative of philosophical or epistemological differences in how a phenomena is viewed. For example, a technology related adverse event could be considered a user error,



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a use error, a system error or perhaps a mechanical failure or a design flaw (Balka et al. 2007).

Language is far more intractable than technology, and semantics are the lynchpin of interoperability. There have been a number of efforts in the information science research community to address data interoperability (Kottman 1999; Bishr 1997, 1998; Bishr et al. 1999; Laurini 1998; Vckovski 1999; Brodeur et al. 2003; Sheth 1999; Cuthbert 1999; Bisby 2000; Kuhn 2002; Fonseca et al. 2002). Approaches to semantic data interoperability have, however, primarily stressed automated solutions (Schuurman 2002). These have focused on federated data sharing environments, semantic similarities between data sets and ways of using existing software platforms to accommodate data sharing through a component architecture approach as outlined by Kottman (1999); or Schuurman (2002).

The problem with technical approaches to interoperability is that they treat language as a form of mathematics and convert semantic relationships to graphs and networks in which proximity on the graph structure indicates closer meaning (Brodeur et al. 2003; Fabrikant 2000; Peuquet 1983). Using metric symbology to describe relationships between semantics does not address the larger problem of understanding how language is used differently in different situations and contexts. Mapping language using vertices (nodes) and arcs linking the nodes (more distance = greater distance in meaning) assumes the semantics are static and that their meaning is interpreted similarly in different contexts. Moreover, it implies that language is detached from communication. The limitations of these assumptions are seen in the above examples where even between provincial jurisdictions, there is ample difference in meaning of a term like suicide.

Data dictionaries and other methods of fixing the meaning of attribute values have failed because there is no single meaning for a term. Instead, there are many to many relationships between entities and meaning that changes depending on context and groups. The meaning of spatial terms is “not canonical” but relational. Groups of scholars such as population health researchers, for instance, do not directly translate events and spatial phenomena into categories such as “at risk” through a positivist calculus. Rather they work together to develop powerful, domain-specific language to coordinate efforts and to communicate their shared perceptions. Semantic interoperability research, to date, has focused on attribute equivalence, context and domain specific investigations and shared ontologies (Frank and Raubal 1998; Bishr 1998; Laurini 1998; Fonseca 2004; Bittner and Edwards 2001). This calculus is doomed; language is dynamic and a moving target.

### **3. Implications for health researchers and practitioners**

Problems inherent in semantic heterogeneity are not theoretical. They have direct repercussions for health. Consider, for example the case of emergency room (ER)

wait times. The length of time a patient waits prior to being seen in an emergency room is of great concern to Canadians. This measure is being used as an indicator of the health of the health care system (Chan et al. 2001). Reports of long wait times cause panic in communities (Canada Newswire 2004; Guardian 2005; Kirkey 2005; Steyn 2004), and calls for action from health system managers. ER wait times play a significant role in resource allocation decisions in hospitals (Calgary Health Region 2005; McIntosh 2005; Sin 2005; Young 2005). Emergency wait times are also invoked in discussions about poor service, and hospitals that post long wait times come under scrutiny. Publicity of long wait times often sets off a series of programs to rectify long wait times, and senior management of hospitals issue directives to middle management to shorten patient waiting times in the ER. Recent examples of effects of such publicity include opening additional beds (Giuffre 2005), providing improved care outside of hospitals, quicker access to specialists within emergency rooms as well as access to liaison nurses charged with improving communication related to care within emergency rooms, setting up discharge lounges, purchasing new equipment, and improving information systems within emergency departments (Capital Health 2004) and allowing ER triage nurses to order diagnostic tests (Sin 2005). Another response is for managers to engage in data gaming (e.g., making a change to how data are reported or which data are reported in order to show more favourable outcomes). While there are a range of possible responses to ER waiting time data, it is easy to demonstrate that these data are the lynchpin for a number of decisions.

Although data about emergency room wait times has become an actor in health policy debates in Canada and elsewhere, “there is no established standard or definition for measuring ER wait times.”<sup>2</sup> Although the limitations of the emergency room wait time data set are significant, the data are used and do play a significant role in health care debates. A preliminary review of ER wait time data yields a tidy picture—on the surface. Hospitals in Canada report emergency room wait times to the provinces as well as the federal government, who, through the Canadian Institute of Health Information (CIHI) maintains data through two databases (the DAD and NACRS databases, which stand for Discharge Abstract Database and National Ambulatory Care Reporting System). The Canadian Institute of Health Information (CIHI) addresses methodological and procedural issues related to the collection of data, including emergency room waiting times. Some data are shared with the Canadian public about ER wait times by CIHI, and other data can be viewed only by reporting institutions that contribute data. The low level of data transparency between the contributing institutions is quickly ascertained by requesting permissions for and analyzing the data. Further analysis of CIHI ER wait time data and the debates that surround it yield a far messier picture of the data set than one might assume based on its widespread use and political significance. A review of the data quality documentation for the Discharge Abstract Database (CIHI 2003) provides some insights into the limitations of the ER wait time filed within the DAD.



#### 4. Methodological approach

The contextual background into the problems of sharing ER wait time data described here were developed from an in depth reading of the CIHI Data Quality Documentation for the Discharge Abstract Databases (CIHI 2003), followed by e-mail correspondences (e.g., see footnote 2) and phone conversations with staff members involved in collection and reporting of data at the federal level (CIHI).

Our interest in and knowledge of extra-local activities related to emergency room wait times (e.g., policy debates, the role of the Canadian Institute for Health Informatics) is the result of following news stories about ER wait times in the press, tracking the formation and dissolution of Canadian institutions and agencies involved with health informatics over time (e.g., Balka 2003a, b), and participating in local and national health policy forums, all of which were undertaken at the same time that a total of three ethnographic work practice studies were carried out at two different emergency rooms.

Knowledge of local data collection practices, which sparked our interest in CIHI data and led us to the Discharge Abstract Database was gained through in depth ethnographic observation of administrative and nursing staff in a local emergency room (see Sharman 2007 for a detailed overview of that study). During this initial study conducted in 2002–2003, two investigators conducted observations for in excess of 200 h. Ethnographic observations were supplemented by interviews and subsequent participant observation conducted as a research staff member at the facility where our first emergency room study was conducted. This first study combined data collection techniques from ethnographic work practice studies with data collection and analysis techniques from Francophone ergonomics. Notes made during field observations and transcripts of interviews were coded and analyzed with the aid of qualitative data analysis software, using a grounded theory approach. Following our focussed period of data collection in this first ER, conversations with staff responsible for data coding, analysis and reporting of local data, were undertaken with the specific purpose of clarifying issues reported here.

Methods employed in studies conducted in the second ER utilized similar methods, which included intensive periods of field based observation which so far have spanned two years. Studies have been undertaken in an effort to develop an in depth understanding of work practices, which in turn can be used to inform computer system selection and configuration. Data from field observations and interviews (conducted to gain a more detailed understanding of work practices than was possible from observations alone) were coded using a hybrid method which incorporated coding categories which were derived both from our previous work and insights from literature, alongside coding categories which emerged through working with the data. (For more detailed accounts of studies undertaken in the second ER, see Balka and Whitehouse 2007; Balka et al. 2008; Bjorn and Balka 2007; and Bjørn et al. under review). Our work in the first ER led to our

interest in CIHI and the Discharge Abstract Database, and informs our discussion below. Studies conducted in the second ER provided the basis for development of the example discussed in the latter sections of this paper, of a meta-tagging system.

Emergency room wait time (Group 4 Field 10) was a new data element introduced in the fiscal year 2001–2002 data set (CIHI 2003). Wait time in ER is defined as a “derived data element [which] reflects the difference between the date/time of decision to admit and the date/time the patient left ER, measured in hours” (CIHI 2003, p. 14). Five of the 13 reporting provinces/territories do not report their ER wait time data in an ICD 9 layout; and a sixth province does not submit their data to the Discharge abstract Database (DAD). For another five provinces, the ER Wait time is an optional data element. In one province, ER wait time is a mandatory field, and in one province the field is not to be used. Reporting of non-mandatory fields to CIHI is typically low. In those provinces where this was not a mandatory field (all but one as of 2003), the response rate was 34% (CIHI 2003, p. 11).

The CIHI Data Quality Documentation for the Discharge Abstract Databases (CIHI 2003) indicates that ER wait time “may be underestimated for some facilities due to the difficulty in collecting the exact decision to admit time. When the exact decision to admit time is not available, admit time is used as a proxy... [which] may inaccurately reflect wait times for some provinces.” The data quality documentation also suggests that caution should be exercised when analysing this field over time, as there have been historic changes to wait time data elements, and reporting requirements vary among provinces and territories. In addition to historical variation in wait time data elements, considerable variation exists in how data are collected locally, and how those data are reported by individual hospitals and health regions in Canada (regional health provider institutions) in their annual reports (e.g., Ottawa Hospital 2004; University Health Network 2005; Capital Health 2004). For example, through our ethnographic work we learned that in one hospital’s emergency room, 6 different times are recorded on the computerized record: a patient’s arrival time at emergency, the time they are triaged, the time they are taken to an emergency department area other than the waiting room (either the treatment area or acute area), the time a patient is seen by a doctor (an optional data field which doctors enter inconsistently), and the time a request to admit a patient is made. Other hospitals using different information systems (which often play a significant role in determining which data points are collected and which are not) collect times at different intervals in the patient’s ER waiting period.

Although other variables such as patient acuity—an important piece of information in determining whether or not care was compromised by a long wait time—are collected, considerable variability exists in how ER wait time data are reported from province to province and health authority to health authority. For example, the Calgary Health Region (no date) reports some ER wait time data in relation to Canadian Triage Acuity Scores (CTAS), which provide an

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indication of the severity of a patient's health condition. Publicly available data through the University Health Network (2005) reports emergency wait times by service area (e.g., heart and circulation, transplant, etc.), rather than by CTAS score. Some provincial data packaged for public use does not include information about patient acuity, or uses measures other than the CTAS scores, which are now a mandatory data element in the NACRS database.

The Ottawa Hospital reports the length of stay in ER for non-admitted and admitted patients. Rather than reporting an average length of stay however, they report the percentage of patients that remain in the ER for more than 4 h prior to obtaining treatment, or, once a decision to admit has been made, prior to admission (Ottawa Hospital 2004). University Health Network (University Health Network 2005) reports the percentage of patients admitted via the ER whose average wait time to an inpatient bed was greater than 12 h from the decision to admit. Capital Health (2004) reports several aspects of ER wait times, including the average wait times, triage to physician amongst patients classified triage acuity level 3 (of five levels, where CTAS level 1 is the most acute and 5 is the least acute). Data collected include average wait times from begin time or registration time (whichever is sooner) until seen by a provider (physician or if no physician time then nurse time). Like the university health network, Capital Health indicates the source of their data. Further review of ER wait time data gives way to more questions. For example, in Alberta, only those people with valid health numbers are included in ER wait time data. The information system code used as a filter for selecting which records to include in the variable ER wait time includes all scheduled outpatient services provided in emergency departments, as well as emergency services, which overstates use of emergency services and may understate waiting times (for those whose appointments for outpatient services were scheduled) (Government of Alberta 2002).

Much of the variation in what ER wait times actually measure that is outlined above flows from limitations related to variation in computer system from hospital to hospital, and the software run on varied computing platforms that is used as the means through which data are captured. Variation in the meaning of the data from context to context are compounded when data are amalgamated, which in the case of ER wait time data may occur first within a health region, as well as through CIHI's NACRS database. Some of these limitations, although not immediately evident, are documented in CIHI technical notes. One such note, for example, indicates that some variables such as "wait time in emergency are mandatory for certain provinces/territories only" (NACRS 2005). Other limitations to data are documented as well: "wait-time in emergency may be underestimated for some facilities due to the difficulty in collecting the exact decision to admit time. When the exact decision to admit time is not available, admit time is used as a proxy. This may inaccurately reflect wait times for some provinces." Although efforts are underway to stabilize the meaning of ER wait time data, so too are efforts to further redefine the meaning of that data.

In spite of the variability in ER wait time data, the widespread use of ER wait time data suggests that semantic homogeneity is assumed, or at least left largely unquestioned, by end users of that data. While data consistency may be maintained within a single ER, numerous factors (including the use of different computerized administrative and patient record systems from one ER to the next—each of which may require staff to enter different times into a patient's record as the patient moves through the ER) contribute to data inconsistency between facilities. Nonetheless, these data then become the source of the national health system report card data. While the analysts compiling those data may recognize the limitations inherent to the semantic heterogeneity of the data (as discussions about data definitions on the CIHI web site suggest), this nuanced understanding of the data is often lost as the data flow into common use.<sup>3</sup>

A tacit assumption that ER wait times reflect a standard means of data collection and reporting—implicit in the ways that ER wait times are used politically—is part of what gives them the weight that they have, and allows them to function as they do in debates about the allocation of health care resources. Context for the computer systems that serve as the means through which data are collected and analysed about ER wait times, and their de facto status as infrastructure (Bowker and Star 2000) help to obfuscate the significance of how data fields are defined within hospital computer systems.

The case of ER wait time data illustrates both the need for standards and the degree to which they are taken for granted. The absurdity of collecting and reporting data that lacks a common definition speaks to both the taken-for-granted nature of standards and reflects the degree to which the collection and reporting of emergency room wait time data currently reflects local conventions of practice (as well as computer systems in use in local settings, each of which captures time differently).

The vignette above suggests that changes may be warranted at several points in the cycle of data collection and use. For example, it may be possible to improve the quality of data at the point of data collection, and to heighten awareness of issues related to semantic interoperability and the quality of merged data amongst decision makers who rely on data that has been derived from system interoperability and data merging. Although both of these issues warrant further attention, here we are concerned primarily with improving the quality of data at the points where data from multiple sources are integrated for the purposes of analysis.

Our focus here is on outlining mechanisms for explicating semantic heterogeneity, with an end goal of improving data quality at the point of database interoperability. Our hope is that the provision of more detailed explanations of what the data contained in a particular database field refer to could support more nuanced approaches to data analysis. For example, ER wait time data could be disaggregated according to the definitions of fields, (e.g., all hospitals reporting time to see a triage nurse could be grouped together, and all hospitals reporting

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time to see a doctor could be grouped together), and wait time comparisons could be calculated for all facilities using similar data definitions. Moreover, metadata detailing the basis for different definitions could be used to retroactively create a common denominator.

The overview of ER wait time data, and specifically the level of detail included about a single hospital's data collection system, sheds light on the kind of insights that context-based metadata—which capture data about data, based on the experiences of those close to data collection and data stewards—can provide. Karasti et al. (2006, p. 321) have suggested “studying actual practices of data curation and stewardship in order to provide more coherent understandings of e-Science solutions and technologies,” and the examples above illustrate the range of insights that such studies can yield. Karasti et al. suggest that information managers are acutely aware of limitations with existing metadata approaches, which loose layers of informal description when scientific data are stored with only formal metadata. An information manager in their study commented that

we are finding now that the structured metadata is much more useful in terms of producing machine readable information, but the narrative often times contains more information..... The data manager knows a lot about what really are the good and bad aspects of the data because we have handled it, we know what works and what does not. That should be part of the metadata. Because ultimately if you don't write those things down, they are going to get lost. It's stuff that is more valuable than a lot of this other descriptive information about a dataset. I mean in terms of a real quality 'gut feeling' of how good it is, like a 'subjective quality indicator' of some sort.

Below, we provide an overview of extended metadata that focuses on the kinds of questions a context-based metadata system might ask of the data steward. This is followed by a brief discussion of how database ethnographies—can contribute to the resolution of issues related to semantic interoperability in health research and epidemiology.

## **5. What is extended or context-based metadata and how might it help resolve semantic interoperability in health research and epidemiology?**

Extended metadata provide a framework for including context-based metadata with existing data as a way of dimensionalizing attributes so that current and future users can assess the suitability of data for interoperability or comparative purposes. Such ontology-based metadata will also provide historical context for archiving data. Moreover the methodology does not require re-formatting of existing relational databases or metadata formats. It simply builds on current metadata formats by extending the fields to include information about methodological issues related to data collection, procedures used for data cleaning, especially those highlighting the derivation of any fields that resulted

from data transformations or were otherwise derived, and issues related to limitations related to the integration of data across computing platforms. The potential problem of exponentially large datasets is addressed by including only a limited range of metadata with restricted character counts—except for the field: anecdotes. In addition, we envisage that only potentially problematic attributes will have metadata associated with them.

At present metadata—if included at all—is collected using wizards contained within existing software programs. Figure 1 features a frame from a metadata wizard in ESRI ArcGIS software. The wizard collects metadata in a format that is compliant with ISO TC 19115 and is easy to use.

The limitation of this metadata is that it focuses on geometric properties of data such as latitude and longitude and positional accuracy of spatial data. It ignores metadata for any attribute that is not geometric.

We have identified eight fields to extend existing metadata systems such as ISO 19115. Table 1 below lists the eight fields considered necessary to dimensionalize health (and other data).

These fields were chosen to represent the maximum ontological context associated with data while minimizing the amount of intellectual labour associated with collecting and archiving the information. As a group, they constitute the basis for recreating the ontological context for data collection and circumstances that constrain their use. Field one—specification of sampling methodologies—is included to allow the user to understand whether the data

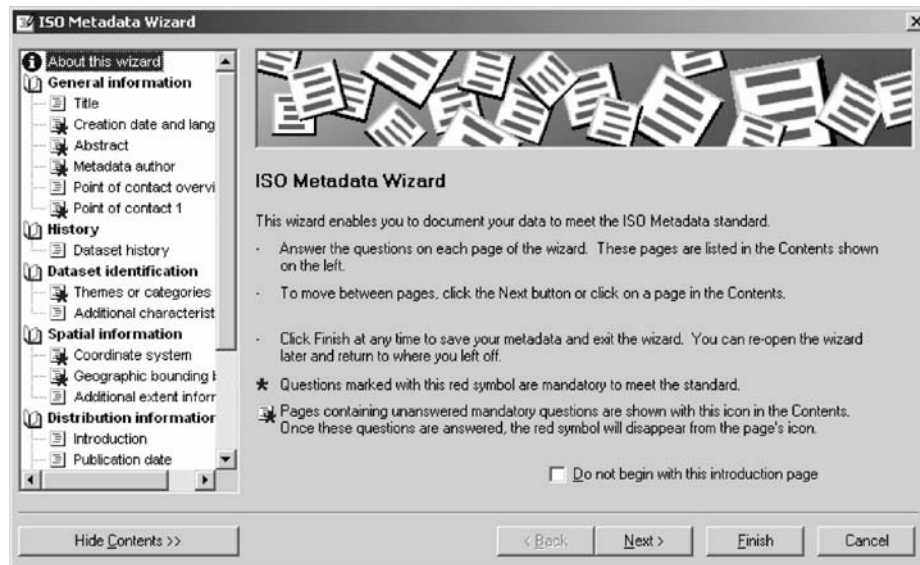


FIGURE 1 Metadata editor for spatial (GIS) data. Note that the metadata fields focus on spatial properties.



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Table 1 Metadata fields for capturing ontological information.

Field	Description
Sampling methodologies	Indication of <i>how</i> data was collected
Definition of variable terms	naming conventions, etc. used to identify and describe entities and attributes
Measurement specification	measurement systems; instrumentation; thresholds as well as range (e.g. clarification of the maximum and minimum)
Classification system	documentation of classification scheme used and taxonomic details; this is the <i>collection</i> of variable terms
Data model	specification of the data model, including history—for example, have different data models been used in the past?
Collection rationale	logics behind data collection and the digital encoding process—an indication of <i>why</i> data was collected in the way that it was
Policy constraints	legal or other constraints or influences on data collection or classification
Anecdotes	additional comments pertinent to understanding how to use the database; not to be confused with <i>abstract</i> , an existing field

This table is based on a table from Schuurman and Leszczynski (2006)

represent a complete sample or if a statistical method was used to generalize from a more limited study. For example, was wait time data collected about every patient entering the ER in a given year, or was a sampling method used, such as every tenth patient? Alternatively, was every patient monitored for a limited period of a week? Were any data excluded (e.g., people without a valid health number) or included (e.g., those who arrived for scheduled appointments in the ER, because the information system could not distinguish between that population and those seeking emergency services). The information contained in this field is the basis for understanding the level of certainty associated with the final data.

Field two addresses what might be considered redundant information. At present, however, many databases contain only cryptic fields (e.g. %FE or Mobile\_H). Despite their evident meaning to the data steward, such truncated descriptions of data are very difficult to interpret. A nurse might understand a field labeled ER wait times to be reflective of time from entrance into the ER to time elapsed prior to contact with the triage nurse. A doctor might understand the same term to mean time elapsed between initial entry into the ER and first point of contact with a physician, or as time elapsed between entry and diagnosis by a physician. Clear definitions of each instance of case would assist greatly in making integration decisions based on this variable. Likewise, a definition of range or gambling-related suicides would provide the basis for use of the variable or determine its suitability for comparison with other—superficially comparable—data.

Measurement specification refers to the way in which the metrics associated with a variable or attribute were ascertained. This is a valuable piece of information that is, at present, seldom included with data. This information has particular value for comparing temporal series when the measurement method may have changed over time. Postal codes may be used to locate schools, hospitals or other services, for instance. These may have originally been linked to individual address data, but subsequently the postal codes may have been assigned based on GPS measurements. Address matching is typically fraught with problems and a 75% “hit” or accuracy rate is considered excellent. Thus the degree of certainty associated with the earlier location data based on addresses may be less reliable than the newer data based on GPS measurements. In the case of ER wait time data, a measurement specification might, for example, indicate whether the data were collected through direct observation, chart abstraction or secondary analysis of administrative computer system records. If derived from a computer based record, measurement data might indicate that ER wait time was derived from a particular field in a particular administrative database, and all cases were included that matched a particular code, and an indication of any changes to coding schema used over time would be included.

Every classification system is a mini-ontology, especially in a digital system. It determines the universe of possibilities for the data that are collected based on a particular taxonomy. Classification, like standardization, is, however, a fraught process. It divides a world comprised of blurred boundaries into separate sets with crisp boundaries (Burrough 1996). Moreover, the classification system is based on a particular epistemological perspective rather than the true range of possibilities. Bias is always evident in the selection of a taxonomy and the definition of its constituent classes. For example, how will the behaviour of people who checked into an ER but, facing a long wait, left before being seen, be classified? Will it be included as a special value in the variable of time elapsed between triage and first contact with a physician? Or will it be reported as a separate variable that belongs to a constellation of variables used to provide insight about ER wait times? Or will it be “cleaned” out of the dataset because no time can be derived if only the start time (but no end time) is recorded?

Field five of the extended metadata scheme moves from the more abstract epistemological plane to that of representation at the data model level. Data models necessarily constrain representation. A raster (or grid cell) representation of spatial data is quite different than a vector (or line-based) representation of the same spatial area (Schuurman 1999, 2004a, b). Moreover the range of analysis available is different within each data model. The schematics are also different for different data models, and they are based on institutional histories and other contingencies. Embedding this information in the extended metadata schema is the basis for enabling data stewards, programmers, and systems analysts to maximize the data value. A data model for ER wait time for example might graphically represent which times are captured through the administrative data set

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that is used to collect and organize the temporal data related to ER wait times. Returning to the example above where one ER computer system allowed the collection of six times related to ER wait, a graphic model might show these six times, might indicate which are reported, and what the variable format is for each variable (e.g., numeric, 6 characters long) and what the acceptable range of values is for each field. Such a model would provide insight into both initial epistemological views of the phenomenon under investigation, and could also assist subsequent researchers in identifying other data that may be available.

The purpose of data collection points to a host of invisible but potent influences on how and why certain fields are included in the end data set. Environmental data collected by a grass roots organization will, for example, contain different biases than those collected by a forestry company for the purpose of illustrating their responsible logging and re-forestation record. Likewise data collected on emergency room wait times by a local advocacy group will likely reflect their goal of reducing the length of time that patients wait to see an attending physician. Data collected by the provincial government that measures the same wait times might construct a different picture depending on the variables chosen and the method in which they are measured. Understanding why a study was designed and what effect that might have had on data selection and collection is important archival information. In cases where data collection has been dictated in part by an underlying computer system, the nature of the computer system and software release should also be mentioned, as this too may contribute bias. For example, ER wait time data collected by hospital administration through a system initially installed to capture billing data is likely to have a different internal architecture and field structure than a computer system installed to support the research functions of ER doctors and other health professionals.

Finally, extended metadata must report transformations to original data. Frequently data are expressed in relation to other information (e.g. rates of incidence) or they are transformed algorithmically. Time presents a simple example of data transformation. Data collection processes may require that temporal data are captured in terms of a start time and end time, but it may need to be reported in terms of total time. This requires a data transformation—start time must be subtracted from end time and expressed either in minutes or portions of hours or days. An equation—or algorithm—must be written to handle this calculation, and it must be able to accommodate things like a patient whose wait spans midnight. It must also be clear how the transformed data are reported—in minutes, hours (or portions thereof). Extended metadata should include information about all fields that result from either transformations or are derived from more than one variable, the algorithms that are used to produce those transformations, and how any unusual circumstances were handled. Such information allows subsequent data users to identify potential error, and alerts them to the existence of data that could be treated differently if required.

In order to collect extended metadata, an ethnographic approach is required (Schuurman and Leszczynski 2006; Schuurman 2008). The goal of database ethnographies is to gather information from data stewards about tacit knowledge so that it can be linked explicitly rather than implicitly with databases. If we think of health registries as data silos—accumulating vast amounts of precious data about individual health conditions but with few mechanisms for sharing—then the only way to find out what each term means in a particular registry context is to talk to those who developed the database format and who act as stewards. Detailed interviews with data stewards must be conducted for each database to be included in an integration and comparison exercise. Whenever possible, data collection activities at the sources where data are collected should be observed, as it is often at the point of data collection that data quality and consistency problems are introduced. It was through in depth observation of data collection activities in an emergency room which occurred during an intensive data collection period of 4 months, supplemented by regular periodic visits and focussed interviews that many of the insights from the ER wait time example above are drawn. In instances where data are processed at an institutional level (e.g., where ER wait time data are abstracted from patient charts by the health records department, for example), interviews should also be conducted with staff involved in coding and aggregation of data at an institutional level, as decisions made within local contexts (such as health records departments or decision support departments) can have a significant impact on subsequent data quality as well as data meaning. As the ethnography of data are written—here meaning the story of how the data are collected and what has happened to them along the way—questions emerge, which are best addressed through follow-up interviews. In the example above, an institutional relationship made it possible to clarify many points and to update information over the telephone. Specific individuals to be interviewed will vary with the context of the database ethnography being conducted, and should include representatives of groups involved in front line data collection, representatives of institutions engaged in coding and reporting data prior to its public release (in the example above, that included staff in the coding area of the health records department who processed ER wait time data into a format where it was reported to the province, who subsequently reported it to CIHI). Finally, any staff engaged in administration of databases such as database administrators, nurse consultants or research staff who may have engaged in hands-on work with the data (e.g., data transformations or re-codes) should also be interviewed. These database ethnographies are the basis for revealing general and specific discrepancies in reporting between health jurisdictions. They also inform potential users about areas of concern when integrating data.

Table 2 below provides a graphic example of what extended metadata might look like for ER wait time data. Text in the table is derived from ethnographic fieldnotes based on observation of work conducted in two emergency rooms. Data collection undertaken for the first case is outlined above. Data collection for

Table 2 Metadata fields for capturing ontological information about ER wait time.

Field	Description
Sampling methodologies	Data collection for all patients. Initial time is a time stamp undertaken when patient goes to the triage desk, subsequently entered into the NCompass admitting and discharge system by a unit clerk. End time is captured by doctor and entered into admitting and discharge system subsequently by unit clerk. Patients leaving prior to being seen or redirected to another hospital (e.g., a Children's hospital) are excluded
Definition of variable terms	Start time = time patient first interacted with triage nurse. End time is recorded on chart by doctor, and subsequently entered into admitting and discard computer system by unit clerk. All times are recorded using a 24 h clock, and date format is mm-dd-yy
Measurement specification	Time values are recorded on a 24 h clock, to the minute. Start time is captured through an automatic time stamping machine. End time is recorded manually according to local wrist watches and clocks. Acceptable time values are from 00:00 to 23:59  Patients who leave prior to being seen are recorded with an end time of 99. Patients who die prior to admission are recorded as 89. Instances where time was not recorded on patients chart by doctor are entered as 79  As admitting and discharge system has been adapted to capture wait time data, it is entered as free text and no value or range checking occurs at entry. Data are subsequently moved to a spreadsheet where calculation of wait time is performed according to an algorithm
Classification system	Wait time is a calculated value which refers to the amount of time that elapses between when a patient first interacts with a triage nurse, and when the patient is first seen by a doctor. It does not capture the time that elapses between when a doctor makes a decision to admit a patient, and when the patient is given a bed. It is reported in # of minutes. The patient's acuity level, measured according to the Canadian Triage Acuity Score (where 1 is most urgent and 5 is least urgent) is also collected and reports of wait times should be reported by acuity level, with reference to the benchmarks established for each CTAS level
Data model	In February 2005 a new means of capturing start time was introduced, with considerable variation occurring throughout February as the new procedure (capturing patient's first encounter with the triage nurse, rather than when patient was triaged by triage nurse) was introduced. On April 1, 2008 a new Emergency Room information system was introduced, which has altered field definitions after that date. The new system is a Cerner product. Data just prior to and after the implementation date should be treated with suspicion as numerous implementation problems occurred
Collection rationale	During a busy flu season when patients often had to wait prior to a full triage assessment, a decision was made to begin data collection at patient's first encounter with the triage desk in order to more accurately reflect length of wait. Facility is required to report data to province who report it to federal government. Data re used locally to inform staffing levels and assess quality

(continued on next page)

*Table 2 (continued)*

Field	Description
Policy constraints	To the greatest extent possible given existing constraints, data collection is undertaken in a manner consistent with Canadian Institute for Health Information data definitions and standards. A requirement introduced by the provincial government limited choice in purchase of the emergency room information system, which resulted in the decision to use the Cerner system
Anecdotes	All cases where no end time is recorded because patient has left should be reviewed with reference to the CTAS score initially recorded by triage staff in order to determine whether or not patients with a probable need for care did not wait, or whether patients with low acuity—who likely did not require emergency care—left Because no range checking or value checking occurs at entry, all outlying times should be reviewed for possible error

Note: The above table presents a hypothetical case constructed from observations of ER wait time data collection in two different facilities.

the second case has spanned two projects in an emergency room over a 2 year period (see Balka and Whitehouse 2007; Balka et al. 2008; Bjorn and Balka 2007; and Bjørn et al. under review), and has recently expanded to include a study of the health records department.

The collection of metadata about ER wait times—as illustrated above—would support the development of more appropriate data comparisons about waiting times in different facilities, and would, for example, make it possible to eliminate all cases where patients checking in for day surgeries through an ER are removed from the larger dataset because they represent a phenomenon that is inconsistent with other definitions of ER wait times. Metadata about ER wait times would make the processes surrounding the creation of the data more transparent to researchers, who, in turn, would be better equipped to present a more accurate view of ER wait times to decision makers. Metadata would help facilities develop an understanding of why their wait times differ from other facilities (e.g., it would make it possible to compare facilities using similar data to one another, and would render the differences in data collected that may be associated with differences in data collection procedures more transparent to the end users of the data). Ideally, increasing the transparency of data collection procedures would also contribute to increased knowledge about data collection and analysis amongst those working with, and using data.

## 6. Conclusion: alt.health.metadata in the real world

Widespread use of ever increasingly sophisticated computer systems makes it possible to both collect more data, and, in a technical sense, more easily share those data. Presently available computer systems are sophisticated enough for us



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to work with large data sets, and often allow us to alter the format of data so that data from multiple sources can be linked, or merged. One consequence is that data are increasingly being used at a distance from local contexts in which data were collected. Indeed, the capture or collection of data—often by multiple individuals in different locations and involved in different parts of processes (e.g., the start time for an ER wait time calculation may be initially recorded by a triage nurse while the end point may be captured by a hospital admitting clerk in another geographic location within the hospital, with the aid of a different computer system) can be thought of as a form of distributed computer supported cooperative work (Balka 2005), and the work required to create metadata (conducting ethnographies about data collection and transformations through observation and interview techniques) can be thought of as a form of scaffolding, required to support the integrity of the data and the decisions which rest upon them.

There are numerous possible approaches to providing context to accompany data attributes in their journeys between institutions and users. The fields of Bioinformatics and Genomics have developed standards for sharing which require all data to be parsed using the specifications of the Gene Ontology (GO). All GO data uses common semantics and the evolution of GO has, in effect, standardized semantics in this field (Schuurman and Leszczynski 2008). This effort falls under the broad rubric of a universal ontology that governs the discipline. Our approach is modular in that there is no controlling body that mandates its use, and individual data managers make the decision about implementation. The extended metadata system reported in this paper, however, does potentially provide a universal standard for metadata fields and their transportation between users and analysts. It is a compromise between universality and piecemeal modularity—and provides a basis for standardized, enhanced sharing of data and meaning.

The examples recounted here demonstrate that while the technology has afforded many possibilities in terms of merging, transforming, linking and sharing datasets, conventions of data use may not have kept pace. In an era where increasing emphasis is placed on evidence in decision making, if evidence is to be meaningful, conventions of data management and use must keep pace with computational possibilities. Extended metadata—data about data that yields a more nuanced understanding of data when it is used at a distance from where it has initially been collected—offers one approach to enhancing the quality and integrity of data. As some of our examples about ER wait time data demonstrate, often some of the information we suggest should be included in extended metadata exists. However, it is often hard to find, and frequently it is not apparent that it exists. Adopting extended metadata can both insure that an appropriate range of information about data sets is captured, and, through graphic techniques, can insure that it is more easily accessible to data users at all levels of use (data stewards through to policy makers). The processes surrounding the creation of metadata can be thought of as database ethnography.

The examples presented above demonstrate how a variety of actors—data stewards, computer systems in emergency rooms, interest groups such as the Canadian Association of Emergency Physicians who are advocating for the use of the Canadian emergency department information system rather than the existing data standard in use by the Canadian Institute of Health Information (CIHI)—are engaged in continual activities that impact the format and meaning of data, and contribute to semantic heterogeneity, which in turn threatens data quality. While in some cases (e.g., Canadian Association of Emergency Physicians) the distance to local policy making may not be great, in other cases (e.g., CIHI, or computer system vendors), actors have structural power and are at a distance from local policy making. Extended metadata provides a means through which we can improve data quality issues that can emerge in the distance between global actors and local contexts of use, and database ethnography provides a means through which we can collect extended metadata, and, in doing so, render visible the dynamic nature of data collection activities, that are often obscured by semantic heterogeneity.

## Notes

1. “Informational continuity reflects the notion that details on past events are available and used to inform current care. Management continuity means that care is clinically consistent over time, that someone is managing the case, or that the management responsibility is efficiently and effectively transferred, and that as a result duplication of procedures and communications are kept to a minimum. Relational continuity means that ongoing patient provider relationships are nurtured in order to bridge healthcare events and create an expectation for future care” (Reid et al. 2004, p.2)
2. Bingham, J. W. (2004, Oct. 29). Director, Health Reports and Analysis Canadian Institute for Health Information. *Personal Communication* (by e-mail).
3. ER wait time data more often than not are reported in the press without reference to CTAS scores, which reflect how ill a patient is, and hence to what extent they urgently require care. For patients who are not ill at all long wait times are not inappropriate. The frequent failure to include CTAS scores in press coverage of ER wait times reflects an overly simplistic understanding of both the politics of health care and the complexities of data.

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