MCHP Data Quality Framework

Manitoba Centre for Health Policy

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"Good decisions require good data."

Introduction

Data collected for various administrative purposes is not always of the best quality for research. Although source agencies often conduct their own quality evaluations, these assessments are unlikely to investigate the data's potential for research use. Multiple other factors affect the research quality of administrative data including the knowledge and experience of data collection staff, the standards and requirements in practice in various work environments, and simply the level of staff distraction on a given day. Use of poor quality data can impede the research process and lead to false conclusions, resulting in the development of programs and policies based on inaccurate or incomplete information. For this reason, it is important to determine the quality of data before decisions are made.

Due to restrictions on when data can be accessed at MCHP, the process of assessing data quality is divided into two phases. In the first phase, which involves working only with one particular set of data files, certain tests are performed by acquisition staff. This is referred to as Acquisition Level analysis. All new repository data at MCHP are evaluated at this level before being installed. This allows Data Management staff to identify problems, document potential issues, and improve the quality of data before it is made available to programmers and researchers. In the second phase, links between data files can occur. At MCHP this is only possible if the analysis takes place within the context of a research project that has received appropriate ethical and Privacy Committee approvals. In this phase analysis concerning Agreement with other databases, Consistency, Measurement Error, and Level of Bias can be implemented.

This framework is a living document that focusses on the formalized process of acquisition level data quality evaluation at MCHP. It is informed by current practices at MCHP as well as "a scoping review of existing [data quality] frameworks" [1] and includes both a general description of the techniques and tools used to evaluate data quality at MCHP and the aim of these tools and techniques. While this document focusses solely on the first phase of Data Quality Evaluation (the Acquisition phase), a summary of both Data Quality Evaluation approaches is provided on the following page.

[1] Lix et al., A Systematic Investigation of Manitoba's Provincial Laboratory Data, 13.

Acquisition Level Quality Assessment

- **Accuracy**
  - **Completeness:** Rate of Missing values, Geographic Coverage
  - **Correctness:** Invalid codes, Invalid dates, Out of range, Outliers and Extreme Observations
  - **Measurement Error**
  - **Level of Bias**
  - **Degree of Consistency**
- **Internal Validity**
  - **Internal Consistency**
  - **Stability across time:** Trend Analysis for core elements
  - **Cross-Walk linkage**
    - **PHIN Validity:** check-digit analysis
    - **Linkability:** Percentage of records that can be linked with other databases
    - **Agreement Analysis:** Using kappa statistics to check consistency of the data with the registry for sex and date of birth.
- **External Validity**
  - **Identifying Units of Analysis (Person, Places, …)**
  - **Level of Agreement with the Literature and Available Reports**
- **Timeliness**
  - **Time to Data Release**
  - **Time to Data Acquirement**
  - **Documentation Currency**
- **Interpretability**
  - **Availability and Quality of Documents, Policies and Procedures, Formats Libraries, Metadata, Data Model Diagrams**
- **Value**
  - **Usage**
  - **User Satisfaction**

Data Quality Framework

Data quality evaluation includes the assessment of accuracy, internal validity, external validity, timeliness, interpretability and value. Each assessment aims to evaluate the usability of the data and is measured by one or more indicators[2]. Using these indicators as guides, macros have been developed to generate summary data for Data Quality Reports, automating and further formalizing MCHP's Data Quality Evaluation Process.

1 The MCHP Data Quality Report

The MCHP Data Quality Report is loosely based on the VODIM (Valid, Other, Default, Invalid, Missing) concept[3] and uses CIHI's suggested indicators along with other indicators uniquely designed for MCHP data. These indicators and their relation to the Data Quality report and Data Quality evaluation at MCHP are outlined below. Data Quality reports are generated for the following intended purposes:

1. Utilization by internal data management staff, as part of the quality assurance process, and the director of that team as an accountability mechanism.
2. Consultation by users of the data including programmers and researchers.
3. To improve the permanent documentation record for this dataset (step 5 in the data management template).
4. As reference for any research projects bringing in new data.

1.1 SAS Data Quality Macros

To keep pace with the large amount of incoming data at MCHP, a series of SAS macros have been developed. These macros facilitate the automatic generation of data quality reports which are then reviewed by MCHP's Data Management group and data providers. In order to encourage collaboration between various organizations and the further development of Data Quality software, these macros have been licensed under a GNU General Public License. The following framework provides a general description of the quality assessments carried out by these macros and the MCHP Data Acquisition team. For a detailed description of each macro and examples of how they are run at MCHP see the Data Quality Macro Manual. For downloadable and distributable copies of these macros please see the Data Quality section of the MCHP website.

[2] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 14.
[3] UK's National Health Services, Data Quality Report for Independent Sector NHS funded treatment Q1 – Q2 2007/08 (Leeds, England: NHS Information Centre, 2008).

2 Acquisition Level Data Quality Assessment

2.1 Accuracy

"Accuracy is the degree to which the data correctly describe the phenomenon they were designed to measure (Arts et al., 2002) or the degree to which data reflect the truth (Iron and Manuel 2007)[4]". This refers to both the completeness of data (absence of missing values), and its correctness with reference to external tables and other sources of documentation. MCHP has used CIHI standards as a guide for both the testing and reporting of data element[5] accuracy.

2.1.1 Completeness

Missing values include blank fields for character variables, periods for numeric variables, and coded missing values. The magnitude of missing values should be identified and reported for all data elements. This type of evaluation is important since, "if selected sub-groups are missing from a database because of exclusions based on age, stage/type of disease or geography… the databases will result in incomplete estimates of the target outcome (e.g. incidence or prevalence)[6]. MCHP uses the following rating for missing values:

MCHP Rating	Item Response Rate
None or minimal	< 5%
Moderate	5-30%
Significant	> 30%

In addition to missing values, completeness of the data can also be measured by examining database exclusions.[7]. It is important that the population for which the data is expected be clearly defined and understood, as the coverage of data can reveal potential data quality issues.[8] If particular populations are not reported in the data based on geography or other characteristics, the data will result in incomplete estimates of the target outcome.[9]

2.1.2 Correctness

Correctness refers to the presence of invalid codes and dates in data and values that are out of range or represent outliers. In order to determine whether values are invalid, documentation and familiarity with the data is required. The different types of invalid values are described below.

Invalid codes: Values of all character variables that do not correspond to the formats (based on codebook documentation).

Invalid dates: Date values that fall outside of a possible or established range. For example, a living person born in the 1500's or a person who died in 9999. At MCHP, invalid dates can be fixed using internal or external imputation (See the Imputation section).

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[4] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 15.
[5] Canadian Institute for Health Information, The CIHI Data Quality Framework 2009 (Ottawa: CIHI, 2009). Accessed on March 13, 2013 at http://www.cihi.ca/CIHI-ext-portal/pdf/internet/DATA_QUALITY_FRAMEWORK_2009_EN.
[6] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 15.
[7] Ibid.
[8] CIHI, The CIHI Data Quality Framework 2009, 27.
[9] Ibid.

Out of range: Values for all non-character variables that fall outside of the valid range (based on the original documentation from the source agencies).

CIHI Suggested Rating	Invalid Values (code/date/out of range) (%)
Minimal or none	Less than 2%
Moderate	2% to 5%
Significant	Greater than 5% to 100%

Outliers and Extreme observations for all numeric variables: The following excerpt by Don Edwards captures the approach to outlier detection adopted by MCHP:

> OUTLIER DETECTION PHILOSOPHY[10]
>
> The term "outlier" is not formally defined. An outlier is simply an unusually extreme value for a variable, given the statistical model in use. What is meant by "unusually extreme" is a matter of opinion, but the operative word here is "unusual"; some extremes are to be expected in any data set. It must also be emphasized, and will be demonstrated, that the "outlier" notion is model-specific: a particular value for a variable might be highly unusual under, say, a linear regression model, but not unusual at all in a model without the regressor. So, outlier detection is part of the process of checking the statistical model assumptions, a process that should be integral to any formal data analysis.
>
> **"Elimination of outliers" should not be a goal of data quality assurance.** Many ecological phenomena naturally produce extreme values, and to eliminate these values simply because they are extreme is tantamount to pretending that the phenomenon is "well-behaved" when it is not. To mindlessly or automatically do so is to study a phenomenon other than the one of interest. The elimination of data contamination is the appropriate phrasing of this data quality assurance goal. Data contamination occurs when a process or phenomenon other than the one of interest affects a variable's value. If this contamination is undetectable at observation time, it can usually only be detected if it produces an outlying value. **Hence, the detection of outliers is an intermediate step in the elimination of contamination**. **Once the outlier is detected, attempts should be made to determine if some contamination is responsible**. This would be a very labor-intensive, expensive step if outliers were not by definition rare. Note also that the investigation of outliers can in some instances be more rewarding than the analysis of the "clean" data: the discovery of penicillin, for example, was the result of a contaminated experiment. If no explanations for a severe outlier can be found, one approach is to formally analyze the data both with and without the outlier(s) and see if conclusions are qualitatively different.

At MCHP the goal is to detect and count the number of potential outliers for numeric variables and report this in a Data Quality Report**.** Suggested methods for detecting outliers from Ron Cody's *Data Cleaning Techniques using SAS* are listed below:[11]

1. **Standard Deviation:** Observations outside of Mean +/- 2*SD will be counted as outliers
2. **Trimmed Standard Deviation:** Observation outside of $Mean_{Trimmed10\%}$ +/- 2*1.49*$SD_{Trimmed10\%}$
3. **Interquartile Range:** Observation outside of (Q1 – k*IQR , Q3 + k*IQR)

[10] Edwards, Don. Data Quality Control/Quality Assurance (Columbia: University of South Carolina, 1998), Accessed March 13, 2013 at http://www.ecoinformatics.org/pubs/guide/edwards.fv4.htm.
[11] Cody, Ron. Cody's Data Cleaning Techniques Using SAS, 2nd ed. (Cary, N.C.: SAS Institute, 2008).

Where:

- Mean is the mean of entire observations
- SD is the standard deviation of entire observations
- $Mean_{Trimmed10\%}$ is the mean of middle 10% of observations
- $SD_{Trimmed10\%}$ is the standard deviation of middle 10% of observations
- Q1 is the first quartile of entire observations
- Q3 is the third quartile of entire observations
- IQR is the interquartile range of entire observations
- k is a multiplier.

The first two methods require an assumption of normality, but the third method is a more non-parametric approach which makes its application more general. Consequently the Interquartile Range (k=2.5) is recommended for detecting outliers.

CIHI Suggested Rating	Outliers Rate (%)
Minimal or none	Less than 2%
Moderate	2% to 5%
Significant	Greater than 5% to 100%

2.1.4 Evaluating Accuracy at MCHP

In order to address potential issues before data quality reports are produced and data is released, the Pre-DQ macro is used to assess new clusters of data. Particularly for datasets with a large number of fields, it can be difficult to detect changes over time such as population of fields, changes in field formats or the loss\addition of fields. The Pre-DQ macro is used to produce a summary report containing the number of values (non-missing) in each variable for two datasets and highlight the decline in number of values (non-missing) in a variable, format changes, and new or dropped variables. This report produces output in excel format.

Pre DQ Example:

Orange implies 0% to 10% drop in number of records

Red implies 10% to 100% drop in number of records

Yellow on "Old vs New Data Type" column implies data type change

Light Green on "Old vs New Data Type" column implies data type is similar but format is different

Latest Cluster Member: VSA_MMDF_2000JAN(MEMNUM=3) ***Previous Cluster member: VSA_MMDF_2000JAN(MEMNUM=2)***

Variables	Previous Cluster Count	Latest Cluster Count	Percent Change	Previous vs Latest Data Type
Var 1	**225**	**220**	**-2.22%**	**Char(4)**
Var 2	79	96	21.52%	Char(6)
Var 3	29	35	20.69%	Char(4)
Var 4	**14**	**11**	**-21.43%**	**Char(4)**
Var 5	**6**	**5**	**-16.67%**	**Char(4)**
Var 6	0	1	100.00%	Char(4)

After data is installed completeness and correctness are assessed at MCHP using the META, INVALID CHECK, and VIMO macros. VIMO is an acronym for Valid, Invalid, Missing Outlier, and is loosely based on a similar data quality assessment conducted by the UK's National Health Service.[12] These macros produce output that can be used to generate the following tables/charts. Outlier, valid, and missing values are reported along with a summary of responses and descriptive statistics for each field. Areas that appear to be incomplete or inaccurate are flagged so they can be further examined by Data Management staff.

Data completeness is also assessed by examining geographical coverage. Geographical coverage is calculated by mapping the Manitoba postal codes for a particular database and reporting the percentage of records by the forward sortation area (FSA), regions with the same first three postal characters. An automated SAS based initiative is currently underway to complete this new quality measure.

2.1.3 Measurement Error

Measurement error occurs when a data element error is attributable to incorrect answers or coding, which can be caused by unclear definitions, lack of training, over editing of data or weakness in data collection procedures. Good documentation and training as well as automated data collection methods can help reduce measurement error. [13]

2.1.4 Level of Bias

The level of bias refers to the when the degree of difference between the "reported values and the values that should have been reported occurs in a systematic way."[14] While true bias is hard to concretely establish other than through re-abstraction studies, possible bias can be detected more easily when sampling errors are occurring, or coverage or responses are not complete. Bias can also occur when a data element is correlated with another, such as the length of observation time with the outcome, known as correlated bias. Correlated bias can be very complex but "can also be easier to detect as values can be compared across elements and differences can be detected."[15]

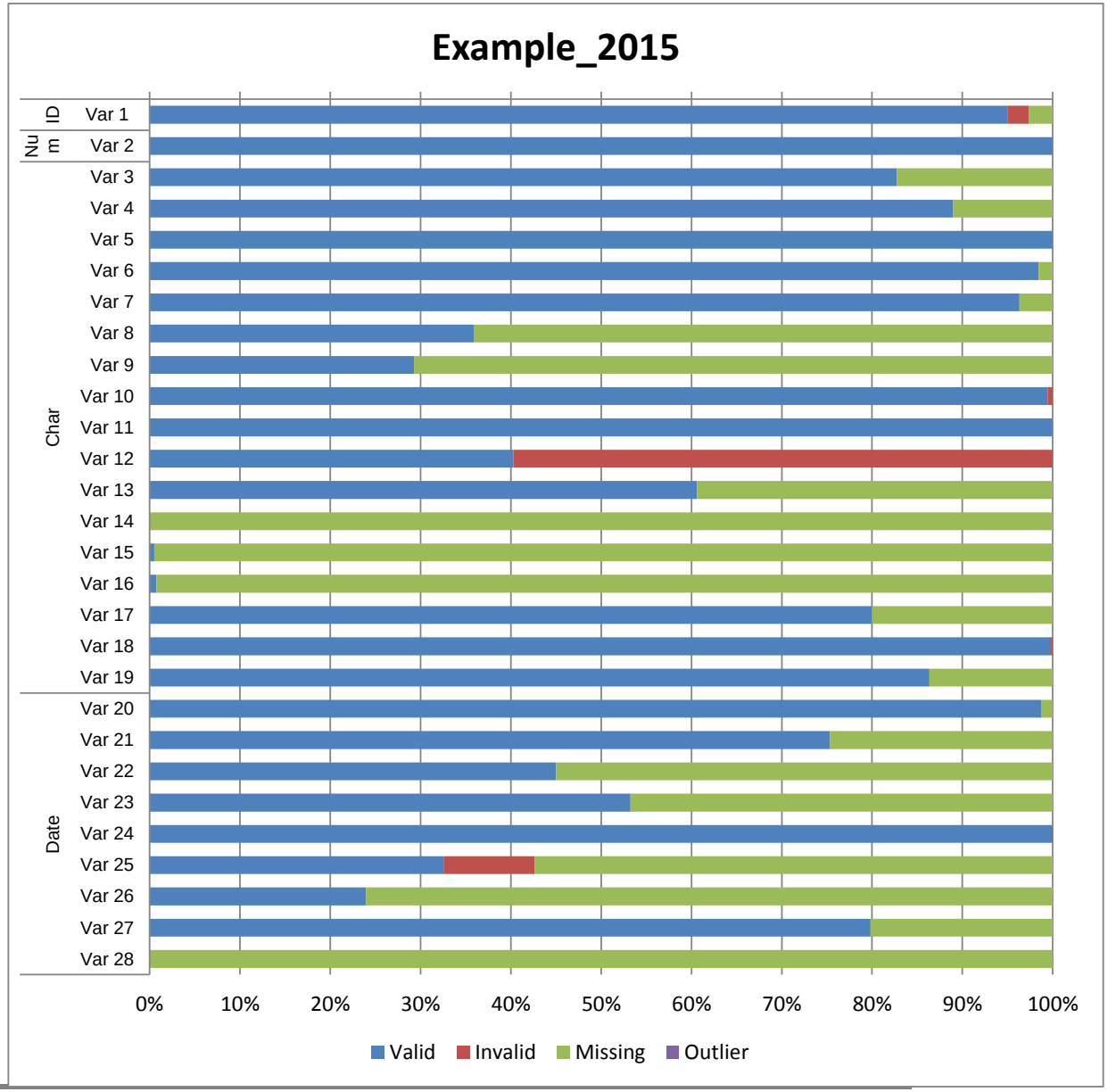
2.1.5 Degree of Consistency

Consistency, also referred to as reliability, is measured by the "amount of variation that would occur if repeated measurements were done." [16] Consistency is often an issue for subjective data elements, ones which may not have a correct answer such as rating a skill on a scale of 1-5, and also when measurement errors occur.[17] Like assessing the level of bias, re-abstraction studies are an effective means of evaluating consistency however, it requires a large amount of resources and is not a means of evaluating for repository data quality at the acquisition stage. Measurement error, level of bias and consistency can be examined for project specific research when it is more relevant to examine data at a more granular level and resources can be allocated for this specific type of data quality assessment.

[12] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 15.
[13] CIHI, pg. 40
[14] CIHI, pg. 41
[15] CIHI, 40
[16] CIHI, pg. 41
[17] Ibid

VIMO Table Example:

	Dataset Label: Example Table		**Records: 2356**			**Legend (Potential Data Quality Problems) :**					
	Dataset Name: Example_2015		**Period: 2002-2015**			**None or Minimal < 5%**	**Moderate 5-30%**	**Significant > 30%**	**Unknown or N/A**		
	= No variance or 100% missing value										
	Legend for comment column										
	Blank = variables have not been tested (no formats have been specified for the variables)										
	✓ = Variables have been tested against the associated formats and no invalid values found										
Type	**Variable Name**	**Variable Label**	**Valid**	**Invalid**	**Missing**	**Outlier**	**Min**	**Max**	**Mean**	**Median**	**STD**	**Comment**
Num ID	Var 1	Label Var 1	95.00	2.40	2.60							
	Var 2	Label Var 2	100.00	.00	.00		0	10	5	5	2.5	
							Top 10 Observed Values					
Char	Var 3	Label Var 3	82.74		17.26		HSC, CGH, GGH, SOH, VGH, SBH					✓
	Var 4	Label Var 4	89.00		11.00		0, 1					✓
	Var 5	Label Var 5	100.00		.00		1					✓
	Var 6	Label Var 6	98.45		1.55		Y6J7K7, H8M9R0, 9H6G4F…					
	Var 7	Label Var 7	96.32		3.68		0, 4					✓
	Var 8	Label Var 8	35.87		64.13		**SUPPRESSED**					
	Var 9	Label Var 9	28.98		70.02		5					
	Var 10	Label Var 10	99.45	.55	.00		N, Y, Unknown					Unknown (290 Invalid Obs. in total)
	Var 11	Label Var 11	100.00		.00		N, Y, DK					
	Var 12	Label Var 12	40.20	59.60	.00		ST, TG, TF, RT					RT (964 Invalid Obs. in total)
	Var 13	Label Var 13	60.63		39.37		0, 1					✓
	Var 14	Label Var 14	.02		99.98		2, 4, 5, 3, 1					
	Var 15	Label Var 15	.50		99.50		2, 3					
	Var 16	Label Var 16	.75		99.25		N,Y					✓
	Var 17	Label Var 17	80.00		20.00		N,Y					✓
	Var 18	Label Var 18	99.80	.20	.00		**SUPRRESSED**					(3456 Invalid Obs. in total)
	Var 19	Label Var 19	86.36		13.64		0,1,2,3,4					✓
Date	Var 20	Label Var 20	98.78		1.22		2011-02-11	2011-02-11				
	Var 21	Label Var 21	75.36		24.64		2005-10-31	2014-03-31				5 invalid obs. out of [2013-01-01, 2014-12-31] range
	Var 22	Label Var 22	45.00		55.00		2011-02-11	2012-09-20				
	Var 23	Label Var 23	53.21		46.71		2011-02-11	2012-09-20				
	Var 24	Label Var 24	99.99	.01	.00		2002-04-08	2011-02-12				
	Var 25	Label Var 25	32.62	10.00	57.38		2002-04-09	2011-02-12				
	Var 26	Label Var 26	23.98		76.02		2002-04-10	2011-02-15				
	Var 27	Label Var 27	79.85		20.15		2011-02-11	2014-03-31				23 invalid obs. out of [2013-01-01, 2014-12-31] range
	Var 28	Label Var 28	.00		100.00		2008-09-30	2014-03-31				150 invalid obs. out of [2013-01-01, 2014-12-31] range


Example_2015
ID
Num
Char
Date
Var 1
Var 2
Var 3
Var 4
Var 5
Var 6
Var 7
Var 8
Var 9
Var 10
Var 11
Var 12
Var 13
Var 14
Var 15
Var 16
Var 17
Var 18
Var 19
Var 20
Var 21
Var 22
Var 23
Var 24
Var 25
Var 26
Var 27
Var 28
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Valid
Invalid
Missing
Outlier

2.2 Internal Validity

Internal Validity relates to the assessment of the internal consistency of the data (e.g. do the values of various data elements relate consistently to one another). Indicators of validity include internal consistency, temporal consistency (trend analysis or changes in data elements over time), and linkability (the ability of two files to link using common keys or identifiers). Methods for detecting and reporting the quality of each of these measures are discussed below.

2.2.1 Internal Consistency

Internal consistency can be measured through numeric agreement or the logical relationships between fields[18]. The internal logic of the data can be used to determine if values make sense. Examples include a 70-year-old woman having a baby, a man having a caesarean section, a 4-year old with an occupation or a hospital with 50 nurses listing a total salary budget of less than $1 million a year.[19]

CIHI Suggested Rating	Degree of Inconsistency (%)
Minimal or none	Less than 2%
Moderate	2% to 5%
Significant	Greater than 5% to 100%

2.2.1a Assessing Internal Consistency at MCHP

MCHP's VALIDATION macro can be used to perform internal consistency checks based on pre-defined criteria. For example, parameters can be written that will check for inconsistencies in the reporting of pregnancy in the following dataset and generate the error table below.

Obs	Admitdt	Sepdt	Sex	Preg	Age
1	25 APR 2011	27 APR 2011	2	1	23
2	26 JAN 2011	25 JAN 2011	2	0	11
3	14 AUG 2010	19 AUG 2010	1	1	34
4	7 AUG 2010	12 AUG 2010	1	0	36

Validation Check for Data Consistency

Count	Error Message	Condition
3	Pregnant Man	Sex ='1' and Preg='1'

[18] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 16.
[19] CIHI, The CIHI Data Quality Framework 2009, 46.

2.2.2 Temporal Consistency (Stability across Time)

Temporal consistency is measured according to the degree by which a set of time–related observations conform to a smooth line or curve over time and the percentage of observations that deviate from that line or curve. This can be assessed using trend analysis.[20]

The documentation provided by CIHI on this subject is particularly enlightening:

> Trend analysis is used to examine changes in core data elements over time. Trend analysis includes comparisons of counts or proportions over time, as well as more sophisticated time series analysis, smoothing, or curve fitting. Graphing data is often particularly helpful for investigating temporal changes. One of the primary rationales for longitudinal analysis is the detection of potential problems in the data as a result of changes in concepts or methodologies.

Note that no change across years may also be an indication of a problem if the data is expected to naturally trend upward or downward due to policies implemented or social or economic changes.

It is important to take into account difficulties involved in producing valid trend estimates. Changes in methodology, inclusion criteria or unit non-response may make it impossible to determine whether the observed changes were real or not. "For example, calculating the total number of admissions from a particular acute care institution may be misleading if mergers or changes in institution type are not taken into account. When determining the number of physicians working in a province, a change in the inclusion criteria, based on the total amount billed to the province, may make past estimates invalid. The following is a general guide for assessing this criterion. "[21]

CIHI Suggested Rating	Guideline
Minimal or none	Little or no problems in producing comparable trends
Moderate	Problems have been identified with some trend data
Significant	Accurate trend data cannot be produced for a core data element
Unknown	Unknown whether accurate trends can be produced

[20] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 16.
[21] CIHI, The CIHI Data Quality Framework 2009, 68.

2.2.2a Assessing Temporal Consistency at MCHP

2.2.2ai Trend Analysis

At MCHP, a SAS macro that can perform a trend analysis for core data elements has been developed. Fields such as the number of hospital admissions or discharges, length of stay, number of tests, fees associated with the physician visits, etc. can be summarized in counts or sums by fiscal year. The macro fits a series of common models and selects the model with the minimum mean square error (MSE), estimates studentized residuals for each observation (with the current observation deleted), and flags significant observations as potential outliers. The macro can also detect repeated observations with the exact same value (indicating no change over time) and will flag these as potential problems. This analysis is described in more detail below through a series of steps:

1. Using PROC FREQ, number of records for a core variable are summarized over fiscal years
2. Fiscal years are coded as 1, 2, 3, …
3. Seven regression models are fitted on the annual number of records:

    a. Simple Linear: $Y=\beta_0 + \beta_1 X$
    b. Quadratic: $Y= \beta_0 + \beta_1 X^2$
    c. Exponential: $Y= \beta_0 + \beta_1 \exp(X)$
    d. Logarithmic: $Y= \beta_0 + \beta_1 \log(X)$
    e. SQRT: $Y= \beta_0 + \beta_1 \sqrt{x}$
    f. Inverse: $Y= \beta_0 + \beta_1 \frac{1}{x}$
    g. Negative Exponential: $Y= \beta_0 + + \beta_1 \text{Exp}(-X)$

4. RMSE (Root Mean Square Error) values for each of the above models are calculated and for each core variable the best fitting model based on the minimum RMSE is selected.
5. SAS calculates "Studentized Residual Without Current Observation" for each chosen model and compares the residuals with the $t_{(.95, n-p-1)}$ distribution, where n is the number of fiscal years and p is number of estimated parameters which is always equal to 2.
6. Observations with absolute studentized residuals greater than +/- $t_{(.95, n-p-1)}$ are flagged as potential outliers.
7. Since no changes over time may be an indication of a problem, SAS also flags identical subsequent observations.
8. SAS also checks for small absolute annual number of records (between 1 and 5 inclusive) and forces them to 3 (the average of all possible small numbers as an estimated value). *It is important to notice that modeling and outlier analysis are done based on the actual annual number of records, but in presenting trend graphs, small numbers are being set to 3 in order to follow MCHP's policy (Any publication or presentation of material must represent more than 5 individuals or events)*
9. Trend graphs along with the fitted model are generated by the SAS Macro (example provided below). Potential outliers, identical subsequent observations and suppressed values are shown in different colors in these trend graphs (Significant outliers in red, identical subsequent observations in orange and suppressed values in green).

2.2.2aii Executive Summary

When new data is acquired a data quality report is generated. This report can then be compared to reports from previous years. An Executive Summary is written by Data Acquisition staff to summarize the year-over-year difference in the data. For example, for a new year of hospital data an Executive Summary may indicate:

- Changes to the size of the population or coverage (adding or subtracting hospitals for example)
- New variables added
- Variables dropped
- Changes to existing variables
- Quality differences between the current and previous year

2.2.3 Linkability

2.2.3a Cross-walk Linkage

Linkability is defined as the ability to link two files using common keys or elements. At MCHP, a record is considered linkable if the record's personal health information number (PHIN) is coded as "individual specific" based on the following table.

PHIN Types	
Individual Specific PHINs	0 MH, verified against concurrent registries 1 MH, redirected to this SCRPHIN from FILEPHIN 2 MCHP, modified sibling's SCRPHIN 3 MCHP, assigned SCRPHIN from Registry 6 MCHP, MH PHIN Not known at MCHP at ACQDT
Record Specific PHINs	4 MCHP, assigned a database specific SCRPHIN 5 MCHP, DB Person ID was not included in crosswalk process 7 HCN is not Manitoba Resident 8 Missing, unspecified or MH SCRPHIN invalid 9 System, not individual SCRPHIN

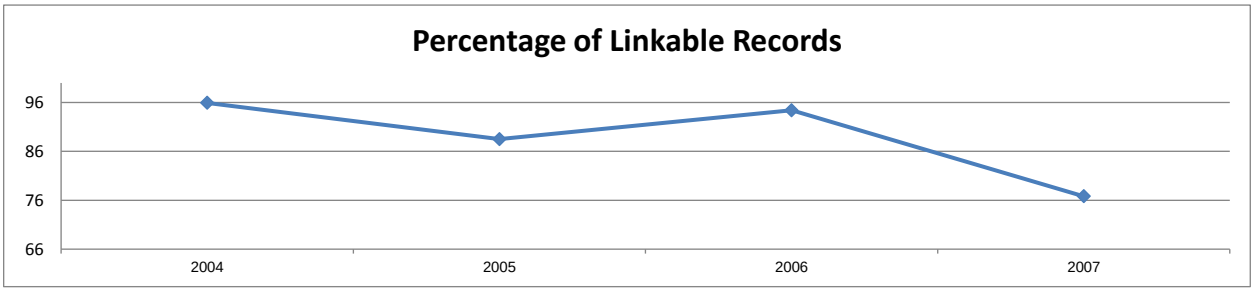
2.2.3ai Cross-Walk Linkage Assessment at MCHP

Tests to determine the status of a PHIN in the dataset are performed at the time the data is acquired by MCHP using the LINK and LINKYR macros. These macros generate output by analyzing the dataset PHIN against the registry PHIN which can be used to create the following charts:

Cross-Walk Linkage

Linkability

Dataset	Total Number of Records	Number of Linkable Records	% Linkable Records	Number of Linkable Individuals
Example_20022005	2986	2496	83.59	2025
Example_20052009	1456	1403	96.35	1398
Example_20092014	897	789	87.95	782



PHIN Types

FILEPHINTYPE	Example Table 1	Example Table 2	Example Table 3
0 MH verified against concurrent registries	83.59	96.35	87.95
4 MCHP db specific ScrPHIN - No MH found	16.41	3.65	12.05

2.2.3b Agreement

Because many linkages are based on probabilistic matches, consistency can be tested using kappa statistics to evaluate agreement for sex and date of birth with registry files (this evaluation is only possible for records with individual specific PHINs).

CIHI Suggested Rating	Degree of Discrepancy with Registry (%)(Separate tables for sex and date of birth)
Minimal or none	0.81 <= Kappa <= 1.00
Moderate	0.50 <= Kappa <= 0.80
Significant	Less than 0.50

2.2.3ai Agreement Evaluation at MCHP

At MCHP agreement is assessed using the AGREEMENT macro. This macro generates output that provides the following details:

Agreement Table

Dataset Name	Degree of Agreement with Registry - Sex (Kappa Statistic)	Degree of Agreement with Registry - DOB (kappa Statistic)
Table 1	0.9779	0.942
Table 2	0.9721	0.948
Table 3	0.97	0.9463

2.2.3c Referential Integrity

Referential integrity refers to the linkability of records between tables within a given database. Identifying orphan values (foreign or primary keys that are not present in a corresponding table) can help Data Management staff to recognize potential problems in the data that may affect analysis.

2.2.3ci Referential Integrity Assessment at MCHP

The referential integrity of the database is assessed using the REFERENTIAL INTEGRITY macro. The following tables demonstrate sample output from this macro:

PRIMARY KEY: CLIENT_VISIT_GUID

Primary Table	Duplicate	Missing	Total Records
CLIENT_2014	124 (x2)	0	108347
	1 (x3)		

FOREIGN KEY: CLIENT_VISIT_GUID

Primary Table	ORPHAN VALUES	Total Records
STATUS_2014	399	29876125
PROVIDER_2014	400	6123543
NACRS_2014	188	583465
CONSULTS_2014	111	171534

2.3 External Validity

2.3.1 Identifying Units of Analysis

"External validity of data can sometimes be quantified by comparison with a "gold standard," that is, an external data source that contains error-free information about the measure or construct under investigation. Sensitivity, specificity, positive and negative predictive values, and likelihood ratio statistics are used to quantify validity. In the absence of a gold standard or when the gold standard contains measurement error, validity can be quantified using specialized statistical models such as latent class models (Bernatsky et al., 2005)" [22].

2.3.2 Level of Agreement with the Literature and Available Reports

Literature, reports, and general knowledge of the data can also be used to assess external validity. For example, in Home Care data higher rates of use among populations recently discharged from the hospital and populations awaiting admission to a nursing home would be expected. In Family Services data, individuals and families receiving income security payments would be expected to be concentrated in postal code areas with low mean household incomes. If the data differs from these findings this may indicate a data quality issue exists.

2.3.3 Level of Agreement with Other Databases

For project –specific data quality, the level of agreement between databases can be assessed after approvals have been put in place. Level of agreement can be measured between two fields measuring the same occurrence or event, or between two databases containing the same unique identifier. If significant inconsistencies between databases exist it can indicate a data quality issue.

2.4 Timeliness

Timeliness refers primarily to how up-to-date the data are at the time of release. At MCHP currency of data is evaluated using three measures: time to acquisition, time to data release and currency of documentation.

2.4.1 Time to Acquisition

The gap between the last reference date in the data and the date the data was acquired at MCHP is an external delay. The variable ACQDT (acquire date) which is a required field in all SPDS data files can be used to calculate this delay.

2.4. 2 Time to Release

The gap between the date that data was acquired at MCHP and the date the data is being released for MCHP users is an internal delay.

2.4.3 Currency of Documentation

[12] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 16.

Documentation currency refers to the time between data installation and the availability of data quality documentation.

2.5 Interpretability

"Changes in program inclusion criteria, data collection methods, or reporting criteria may confound an analyst or researcher's ability to identify data quality problems"[23]. For this reason, the quality of historical and concurrent documentation for each data file is also important. Certain values or codes, increases or decreases in the total number of records, and outliers may be falsely marked as data quality issues as a result of poor documentation (e.g. undocumented changes to formats, valid ranges, or eligibility criteria). Interpretability is defined as the ease with which the user is able to understand and utilize the data properly.[24] Only with the support of proper documentation is it possible to establish whether a data quality problem truly exists.

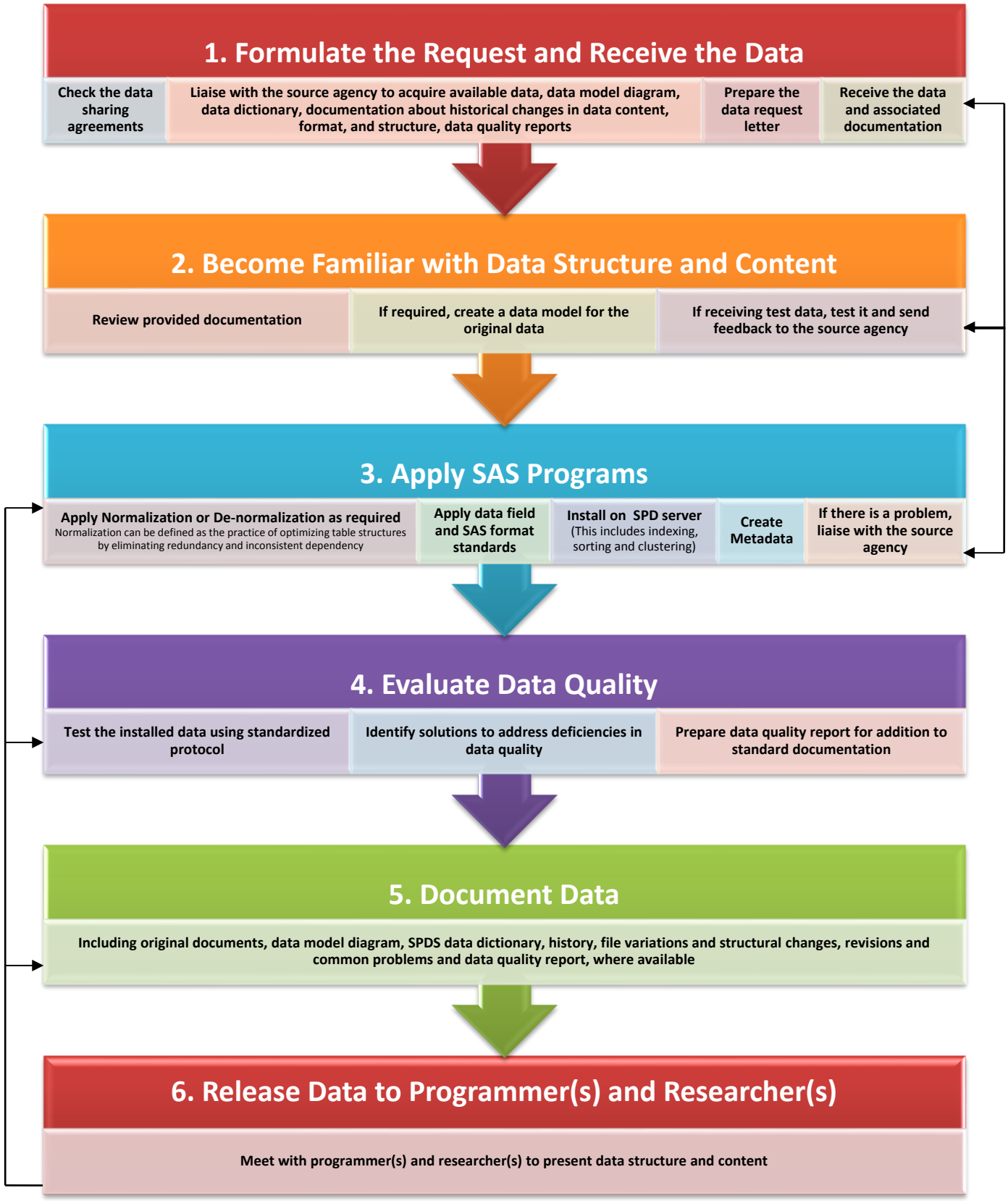
3 Dealing with Problems in the Data

3.1 Imputation

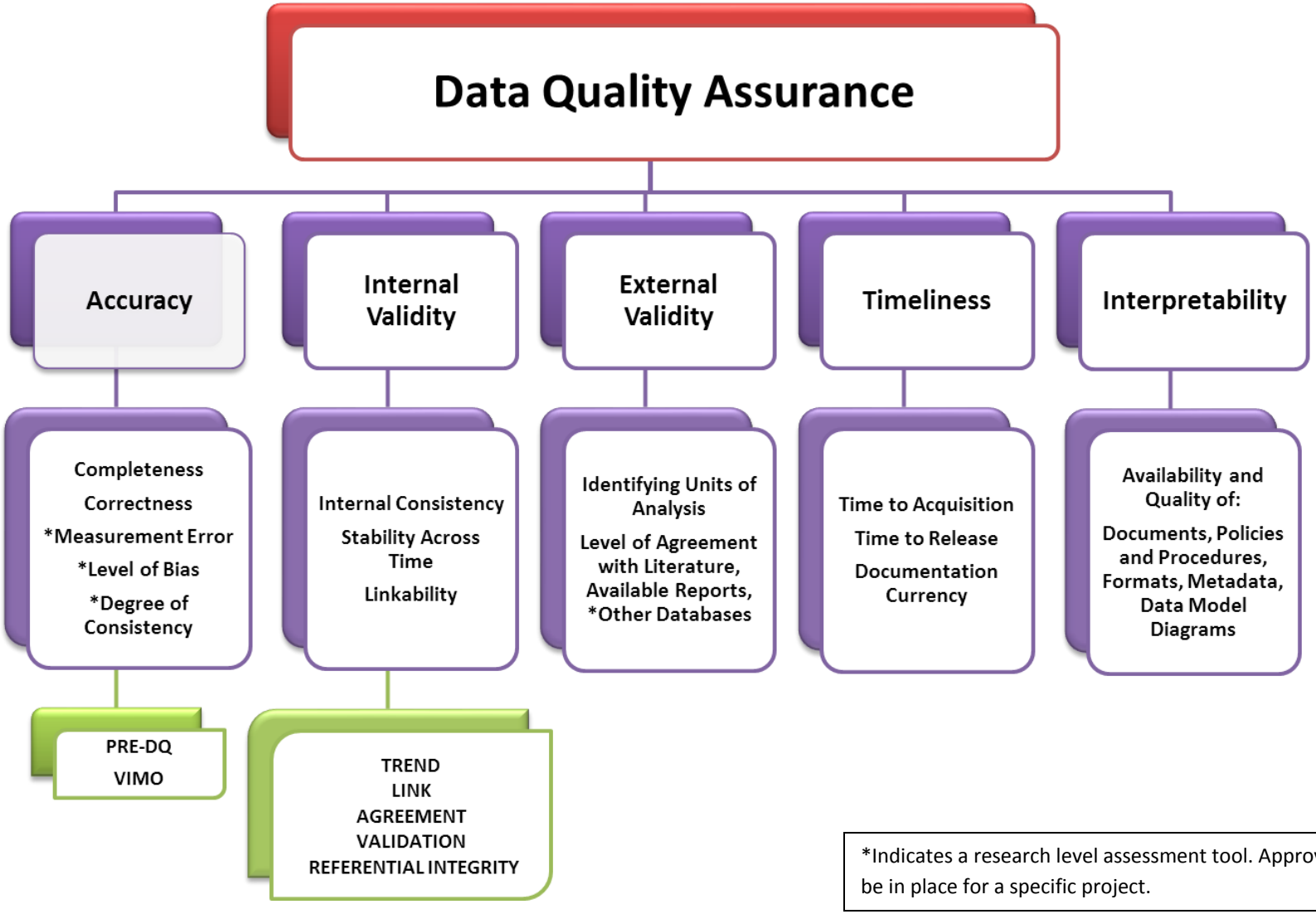
Imputation is the process of determining and assigning replacement values for incorrect or missing data.[25] Imputations can be either internally or externally derived. An internal imputation is the process of replacing incorrect or missing data using information from the dataset being assessed. In external imputation, replacement values are taken from other datasets. At MCHP external imputation is only permitted for data files in the same domain. For example, missing SEX values in the Medical Claims files may be imputed using the Manitoba Registry because both databases are part of the 'Manitoba Health' domain. However, the same imputation for Manitoba Schools data would not be allowed because it falls under a different domain (Education). Imputations may only be applied where there is strong and convincing evidence. All imputations must also be clearly documented.

[23] Lix et al., A Systematic Investigation of Manitoba's Laboratory Data, 17.
[24] Australian Bureau of Statistics, "ABS Data Quality Framework," (Canberra, Australia: Australian Bureau of Statistics, 2009). Accessed on April 24, 2015 at http://www.abs.gov.au/AUSSTATS/abs@.nsf/Latestproducts/1520.0Main%20Features1May%202009?opendocument&tabname=Summary&prodno=1520.0&issue=May%202009&num=&view=.
[25] CIHI, The CIHI Data Quality Framework 2009, 45.

Appendix A: The Data Management Process Diagram



Appendix B: The Data Quality Process Diagram



*Indicates a research level assessment tool. Approvals must be in place for a specific project.

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