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Data Quality and Analysis: Managing and Using Home and Community-based Services Data for Quality Improvement

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Recommended Citation

Fralich, J., Booth, M., & Keith, R. (2006). Data quality and analysis: Managing and using home and community-based services data for quality improvement. New Brunswick, NJ: The Community Living Exchange Collaborative at Rutgers Center for State Health Policy and the National Academy for State Health Policy.

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Data Quality and Analysis
***Managing and Using Home and
Community-Based Services Data for
Quality Improvement***

April 2006



UNIVERSITY OF
SOUTHERN MAINE



Rutgers Center for
State Health Policy

April 2006

Discussion Paper

Community Living Exchange

Funded by Centers for Medicare & Medicaid Services (CMS)

Data Quality and Analysis: Managing and Using Home and Community-Based Services Data for Quality Improvement

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The Community Living Exchange at Rutgers/NASHP provides technical assistance to the Real Choice Systems Change grantees funded by the Centers for Medicare & Medicaid Services.

We collaborate with multiple technical assistance partners, including ILRU, the Muskie School of Public Service, National Disability Institute, Auerbach Consulting Inc., and many others around the nation.

This document was developed under Grant No. 11-P-92015/2-01 from the U.S. Department of Health and Human Services, Centers for Medicare & Medicaid Services. However, these contents do not necessarily represent the policy of the U.S. Department of Health and Human Services, and you should not assume endorsement by the Federal government. Please include this disclaimer whenever copying or using all or any part of this document in dissemination activities.

Acknowledgements

The authors would like to acknowledge the work of the Muskie School data quality workgroup which prepared *A Guide To Effective Data Management In Applied Research Projects*. We have used many of the concepts and recommended practices from this document in this paper.

In particular, we would like to acknowledge and thank Catherine McGuire, Louise Olsen, Kim Murray and Michel Lahti for their thoughtful comments and input on this paper. We would also like to recognize the other research staff at the Muskie School who participated in the data quality work group including Tom Gray, Teresa Hubley, Stephanie Loux, Sameer Mahimkar and George Shaler.

The authors also want to acknowledge the 2003 Systems Change QA/QI grantees for reviewing drafts of this document to assure its relevance to their quality management activities. Our monthly conference calls together remind us of the challenges states face in their daily efforts to improve the quality of their HCBS programs. This technical assistance brief is a product of grantee willingness to share expertise, ideas, and tools so that others can benefit from their experience.

Finally, special thanks to Lisa Marie Lindenschmidt for her formatting suggestions and attention to detail.

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Managing and Using Data for Quality Improvement

The Data Management and Use Series represents the third in a group of papers synthesizing the ideas and practices of states as they improve the quality of home and community based services (HCBS) and supports for older persons and persons with disabilities.

In 2003, the Centers for Medicare & Medicaid Services (CMS) awarded grants to 19 states to enhance their quality management (QM) programs for HCBS programs.¹ CMS contracted with the Community Living Exchange Collaborative² to assist states in their grant activities by promoting information exchange and facilitating discussions on topics of common interest. As part of its work with the Community Living Exchange Collaborative, the Muskie School of Public Service, together with grantee states, identified three initial priority topics for working papers:

1. Quality Management (QM) Roles and Responsibilities
2. Discovery Methods for Remediation and Quality Improvement
3. **Managing and Using Data for Quality Improvement**

The Data Management and Use Series builds upon the concepts and techniques discussed in the two previous papers and provides additional resources for states as they seek to organize, analyze and report data in a way that informs decision making and supports quality management and improvement.

Focus and Purpose of Data Use and Management Series

The focus of many QA/QI Systems Change grantees is the collection and automation of HCBS waiver data for use in program and outcome improvement initiatives. Challenges remain however on how to use the data that are collected and report information that is timely, accurate and cost-effective. States are challenged to integrate information from of a variety of separate systems and present data in a format that is meaningful, purpose-driven and often dependent on the audience or stakeholder. CMS's requirement that states report data in a way that directly addresses HCBS waiver assurances gives each of these challenges additional weight.

A number of specific issues and questions were identified through monthly conference calls and one-on-one discussions with grantees. These include the following:

- **Performance Measurement:** How do states construct and use performance measures to evaluate HCBS programs?
- **Data Quality and Analysis:** How do states validate, clean and analyze waiver data in a way that supports project management and informs decision-making?
- **Data Presentation:** What types of tables, charts and graphics are used to present data, and how does the effectiveness of these formats vary depending on the type of information and/or pattern being conveyed?
- **Reporting:** What types of reports are generated from HCBS waiver data and how do these reports vary depending on the audience and purpose?

¹ QA/QI grantee states include: California, Colorado, Connecticut, Delaware, Georgia, Indiana, Maine, Minnesota, Missouri, North Carolina, New York, Ohio, Oregon, Pennsylvania, South Carolina, Tennessee, Texas, Wisconsin, and West Virginia.

²The Community Living Exchange Collaborative is a partnership of the Rutgers Center for Health Policy, the National Academy for State Health Policy and Independent Living Research Utilization. Under contract with the Technical Exchange Collaborative, the Muskie School of Public Service is the lead for providing technical assistance in the area of quality assurance/quality improvement.

- **Data Integration:** How is data from different sources blended and linked to create a larger and more comprehensive data environment?

This paper reports on data quality and analysis from a program manager's perspective. It is not meant to be an exhaustive research document, nor is it intended to single out any one correct approach. The paper is meant to facilitate communication between program units and analytic staff and serve as one reference for states as they continue to improve upon data collection techniques and use this information for ongoing quality management and improvement.

Data Quality and Analysis

The increased use of data to inform policy and improve practice requires a renewed emphasis on assuring the underlying accuracy and reliability of data. High quality data are critical for decision making, priority setting, and ongoing monitoring of programs and policies. Poor quality, inaccurate or inadequate data can lead to inappropriate assumptions, misleading results, bias and ultimately poor policy and decision making.

The management of data quality is a process that begins with the design of the data collection and data entry process. It continues with analysis of the data after it is collected and the preparation of data for report presentation. A previous paper on Discovery Methods in Home and Community Based Programs (Fralich, Booth, Gray, et al., 2005) focused on the features of a reliable and robust system of data collection and data entry.

The purpose of this paper is to sensitize and inform program managers about the processes involved in data quality management. In many instances, program managers may rely on other technical staff, either within their agency or outside the agency (e.g., an IT department or contractor) to actually conduct the technical aspects of data import, cleaning and analysis. Nevertheless, it is important for a program manager to understand the process of data quality management and to provide the time and resources necessary to produce reliable and accurate data. The process of validating and cleaning data is often the most time consuming and resource intensive part of the data collection and analysis process. While the examples and focus of this paper relate primarily to home and community based programs, the concepts are applicable to many other programs that involve data analysis.

This paper focuses on ways to assure the accuracy of data, discusses tools for analyzing trends and patterns in data and provides tips on interpreting the results of data analysis.

The primary goals of the data quality and analysis process are:

- to validate data;
- to clean data;
- to explore and examine patterns in data;
- to understand the uses and limitations of data; and
- to interpret the results of the data analysis.

Definitions

For purposes of this paper, the following terms and definitions are used:

File: A program, document, or dataset physically stored on a network or local drive.

Record: A single observation/row in a dataset. It is often an individual person but depending on the dataset, it could also be a medical claim, a geographic unit, an organization or other unit of analysis. For example, in a data set of consumer survey results, each consumer survey is a record. A record represents an entity with certain field values.

Field: An element of a database record in which one piece of information is stored. In a dataset, it is a single column. Fields are also called variables because they can “vary” for each observation in the dataset. In the consumer survey example, each question on the survey represents a field or variable.

Value: The numeric or categorical contents of a single cell in a dataset. For example, “12” is the value of an individual person’s highest year of school if they have graduated from high school. In a consumer survey, the answer to a question on the survey (*e.g.*, yes, no, unsure) is the value in the field.

Continuous variable: A variable that can take any value between the valid low and high options for that variable. For example, the valid low and high number for a person’s age can be any number between 0 to over 100 (*e.g.*, age 40; 53.25; 65). Similarly, a person can earn a salary that ranges from 0 to theoretically infinity.

Categorical variable: Variables that are not continuous (gender, race, highest degree completed, age group) may be called “categorical” or “discrete.”

Data set: A collection of observations (records) and variables (fields), usually in table format, which describes the characteristics of a specified group of individuals, organizations, medical visits, or other unit of analysis.

Data Validation

There are many ways for errors and other problems to find their way into datasets during data collection and transmission. Thus the first step in analyzing new data should be to validate it, that is, to verify that the data appears reasonable and consistent with the documentation that describes it. Data validation includes:

- checking the data for completeness and consistency with original documents;
- identifying missing values;
- identifying missing records;
- examining patterns that suggest incorrect, unlikely or missing values; and
- determining the existence of inappropriate duplication.

The following chart provides examples of the potential problems that can be encountered and some of the questions to ask when first analyzing data. The examples relate to data collected as part of a consumer survey but are applicable to other datasets as well.

Issue	Question (for consumer surveys)
Missing/Duplicate Records	<ul style="list-style-type: none"> Does the number of records in the data base equal the number of surveys completed?
Missing values	<ul style="list-style-type: none"> How many/which variables have missing values (<i>e.g.</i>, value in the field is blank or coded with “no response”to the question). If there are missing values (blanks), do you know why?
Incorrect source data	<ul style="list-style-type: none"> Do the general patterns of answers to the questions make sense, seem reasonable, appear to be what you expected?
Incorrect coding	<ul style="list-style-type: none"> Are any of the values outside a range that you would expect? For example: if age is a question on the survey, do the ages make sense given what you know about the populations?
Data import errors	<ul style="list-style-type: none"> Do the characteristics of the people who completed the survey make sense? (<i>e.g.</i>, ranges; male/female; percent of questions answered by participant versus other; number records with missing values)
Problems with data collection tool	<ul style="list-style-type: none"> Are there any questions where there are a high number of unsure or no responses coded? Have you talked with people who conducted the interviews to determine if any questions were confusing or misunderstood?
Inconsistent Coding	<ul style="list-style-type: none"> Are there answers to questions that are inconsistent? Examine the questions on the survey to see if there are ways to check on patterns to answers to questions.
Skip Patterns	<ul style="list-style-type: none"> Does the questionnaire have skip patterns (<i>e.g.</i>, follow-up questions that are only answered if a first question is answered)? Are there answers to questions that should have been skipped?
Other Cross Checks	<ul style="list-style-type: none"> Find other ways to cross check data items for consistency and logic.

Data Cleaning

Where problems with individual files and variables are identified in the validation process, these must be dealt with in some way before further analysis of the data can proceed. This step, called “data cleaning,” usually involves eliminating duplicate records, resolving missing values, and modifying or marking incorrect or unlikely values.

The most common types of problems that require data cleaning are:

Problems with Source Data

When problems are identified, the original source data should be checked and compared with the imported data to determine whether these problems existed in the original files/documents or whether the problems arose in the import process. If the problem appears to be a question of the original documents or data entry, it may be necessary to examine some of the original data files and/or talk with those involved in the data collection/data entry process. If the problems arose during the data import process, it may be necessary to deal with or correct the problems during the data cleaning process.

Duplicate Records

Exact duplicates, where the value in every field is the same on both records, are most likely to occur in the transmission process when an error results in the same set of records being copied twice. Most

database management software includes easily used methods for getting rid of exact duplicates and this should usually be done, since in most cases it involves no loss of actual data.

Missing Values

Missing or null values indicate the absence of any value in a field (*e.g.*, the field is blank). For instance, a survey may include a skip pattern where certain questions are not answered. Missing values may also occur if a person declines to answer a question on a survey or if an interviewer fails to record an answer on the survey instrument. In some data sets, missing values have a specific code assigned to the field to assure data integrity.

Missing values are usually treated differently depending on whether a variable is continuous or categorical. Most statistical software excludes records where the value of a specific continuous variable is missing from all calculations using that variable. In some cases, records with a large percentage of missing values may be removed from the data set altogether.

For categorical variables, treatment of missing values depends on the purpose of the analysis. In some cases, it may be better to exclude observations where a specific variable is missing, but in others it may be appropriate to include them with a value of “unknown”. Where check-off boxes have been used to record yes/no responses to survey questions, the presence of a check indicates a “yes”, but the absence of a check (a missing value) may not always distinguish between “no” and “no response”. In this case, it may make sense to recode the missing values as zeros, but the individual survey questions should be evaluated before doing this.

Treatment of missing values during the cleaning process is an important part of the analysis. The method that is adopted will depend in part on how the data is to be used. In any event, there should be documentation of how missing values are treated and this should be included in the notes of any report.

Treatment of Missing Values: Participant Experience Survey

The Participant Experience Survey is a consumer survey instrument that is designed to find out about the experiences and satisfaction of people who receive home and community based services. The instrument includes the following response categories to its questions: unsure; unclear; no response. Responses coded as unsure, unclear, no response are excluded from the computation of the quality indicators.

For more information, visit:
http://www.cms.hhs.gov/HCBS/downloads/4_PESUG_ED.pdf

Treatment of Missing Values: National Core Indicators

The National Core Indicator Consumer survey is a survey instrument that is used to find out about the experience of people with developmental disabilities. The National Core Indicator Survey has 2 sections.

Section I of the survey includes questions aimed at obtaining opinions from each individual and may be completed only through direct interview; proxy responses are not acceptable. A person's responses are excluded if: the consumer responds to less than half the questions; the interviewer records that the person did not understand the question; or the interviewer records that the person gives inconsistent responses.

Section II of the survey allows multiple respondents. Questions are to be answered by the individual if possible. If the person is unable to respond, an advocate is asked to answer. If a respondent is excluded from Section I, his or her responses are excluded from Section II. Otherwise, all responses (by the consumer or a proxy) are included in the analysis, regardless of how many questions were answered.

For more information, visit:

http://www.hsri.org/docs/786_P6_Consumer2004_final.pdf

Incorrect Values

When the validation process identifies cases of impossible, unlikely, and conflicting data, these need to be resolved during data cleaning. Doing this usually involves changing the value to missing; in limited cases, correcting it with more reasonable values based on other data in the file; or omitting the either the record or the field from analysis. As with missing values, this may require resolution on an individual case-by-case basis. Common cases include:

Impossible values: Some values for a variable may fall outside of a defined range of possible values (for example a 500 year-old patient) or because they conflict with the evidence provided by other variables (a five-year-old male receiving obstetric care). In most cases such incorrect values should be set to missing or (for categorical variables) changed to a value that indicates that the original value was identified as incorrect.

Correctable values: In a rare cases, other evidence may suggest what the correct value should be. In all cases the decision to replace an incorrect value with a reasonable guess rather than a missing value should take into consideration the nature of the research or analysis and the potential impact on the analysis. In general, data should only be corrected if there is valid data from another source that can be used to corroborate the corrected value.

Outliers: With continuous variables a value may fall so far outside the range of all the other observations as to seem highly unlikely. Extreme outliers are important to deal with in statistical analyses because they frequently have a very strong impact on the results, and depending on the research or analysis, they should either be reset to missing or their presence in the data should be flagged by creating a new variable so that the entire record can be excluded for certain analyses.

Data Exploration and Pattern Analysis

Once the data files have been validated and cleaned, a preliminary process of exploratory data analysis is often conducted. Data exploration is the process of discovering the structure in a dataset using statistical summaries, visualization and other means. The methods used to conduct exploratory data analysis can be used to validate and clean data as well as to understand and interpret the data. These are usually conducted using statistical software packages. As a program manager, you may want to request or ask to see results from these types of analysis.

Frequency Distributions

A frequency distribution gives the frequency (percentage) calculation for each variable. For example, a frequency distribution for the answers to the questions on a consumer survey would be:

Question (N=100)	Yes	No	Unsure	Unclear	No Response	Total
Did you receive information on how to file an appeal?	75%	10%	8%	5%	2%	100%
Did you participate as much as you wanted in developing your plan of care?	85%	10%	2%	1%	2%	100%

A frequency distribution from an Access database used to store the results of a record review process might include:

Question (N=50)	Yes	No	Unclear	Missing	Total
Was the level of care determination accurate?	95%	4%	1%	-	100%
Was the participant service plan complete?	93%	4%	2%	1%	100%
Did participant have any identified risk factors?	45%	40%	10%	5%	100%

Cross-Tabulations

Cross tabulations are used to determine whether observations are fairly evenly distributed across important variables or whether some groups are much larger than others. For example, a cross tabulation can be used to examine differences in the answers to questions across counties or across waivers; to examine differences in responses based on participant characteristics (*e.g.*, person lives alone/lives with others). Cross tabulations provide a useful way to look at some of the underlying patterns in your data. The following are examples of some cross tabulation results:

Can you talk to your case manager or support coordinator when you need to?	County 1 (n=100)	County 2 (n=200)	Total (n=300)
Yes	83%	56%	65%
No	10%	10%	10%
Sometimes	5%	20%	15%
Unsure	1%	4%	3%
Unclear response	1%	1%	1%
No response	-	1.5%	1%
Not applicable – have not tried	-	7.5%	5%
Total	100%	100%	100%

Do you ever go without a bath or shower when you need one?	Person does not live alone (n= 215)	Person lives alone (n= 85)	Total (n=300)
Yes	83%	71%	80%
No	5%	24%	10%
Unsure	2%	6%	3%
Unclear	7%	-	5%
No response	3%	-	2%
Total	100%	100%	100%

Did you participate as much as you wanted in developing your service plan?	Waiver 1 (n=395)	Waiver 2 (n=105)	Total (n=500)
Yes	93%	76%	90%
No	1.2%	19%	5%
Unsure	2.5%	4%	3%
Unclear	1.2%	-	1%
No response	1.2%	-	1%
Total	100%	100%	100%

Univariate Statistics

The univariate analysis should be generated for continuous variables and includes a calculation of the mean, median, minimum and maximum. An example of univariate statistics using payment data is:

Waiver cost per person					
	N	Mean	Median	Minimum	Maximum
Waiver 1	1000	2200	2100	200	4400

Emergency Room Visits in Year 2000					
	N	Mean	Median	Minimum	Maximum
Waiver 1	71	2.15	2.0	0	7
Waiver 2	305	1.84	1.0	0	14
Waiver 3	119	1.98	1.0	0	78
Waiver 4	1234	1.59	1.0	0	12

Data Documentation

As information is gathered from the data validation process and decisions are made with respect to data cleaning and treatment of missing values, etc, it is essential to keep an ongoing record of the issues, and decisions that are made. Many of these will become part of the documentation and footnotes in the final reporting of the data.

Data Quality Review

Another critical component of data quality management is to include a process for reviewing, critiquing and checking the results of any analysis. This can include a review of the “code” in a software program, checking the formulas in an excel spreadsheet, proof reading and discussing results of preliminary analysis, and/or review of draft reports for typographical errors, computation, or transposition errors. It is helpful to identify one or more people who can perform this quality review function during the various stages of cleaning and reporting data.

Uses and Limitations of Data

Once data have been validated and cleaned, a first set of data for preliminary reporting is typically produced. At this point, it is helpful to think carefully about the final audience and how the data will be used to inform decision making, shape policy, or monitor performance or activities. This includes consideration of how you want the results of the analysis to be interpreted and what conclusions are reasonable to make from the data. Some of the uses and limitations of data are discussed below.

Sampling Issues

Statistical sample methods: How data were originally collected will determine what conclusions can be drawn from the final analysis. If a statistical sampling method was used to select a sample, this will guide how the results are reported. If a random sample was selected, you should have determined at the outset, the correct size of the sample, in order to provide the desired “degree of confidence” and the desired “error level”. You can then draw conclusions about the entire population based on the results from the sample. The results would be reported such that the reader would know that you have X degree of confidence that the results have an error of no more than Y%. For more information, visit: <http://www.custominsight.com/articles/random-sampling.asp>

Other sampling methods: It may not always be possible or practical to select a sample using a statistical sampling method. For example, it is not uncommon to select a percentage of cases to review or audit based on resource constraints or convenience. In this case, the results of the record review might be used to point to areas for further inquiry or to identify patterns or trends rather than to draw firm summary conclusions.

Subsets of Samples: Another caution concerns the subsets that may be created during the data analysis process. While a sample may have been selected using appropriate statistical techniques, it may not be appropriate to draw conclusions about subsets of the population. For example, it may be possible to examine the statewide results of a consumer survey but the sample size for regions of the state may be too small to report with the same degree of confidence that is applied to the total sample.

Risk Adjustment

In order to make meaningful comparisons between groups and their outcomes of care or services, it is often necessary to “adjust” for the differences in the characteristics of people within those groups (Iezonni, 2003). The reason for this is obvious. Many factors contribute to the outcomes, use and cost of services provided. The characteristics of people in a group (e.g., health condition, age, level of impairment) will influence effectiveness of the services provided and thus the outcomes of those services.

Risk adjustment is an analytic method that “controls for” the degree to which a person is at risk for a particular outcome because of personal characteristics, as distinct from the aspects of care provided by the practitioner or organization. (Fortinsky, 2004). Without some way to adjust for the characteristics of the population (such as mix of people with different diagnoses; levels of impairment), it is difficult to interpret particular outcomes as indicators of quality. Ideally, a risk adjustment should account for factors that cannot be controlled by a provider, but that affect the probability of a particular outcome. (Mukamel, 1997).

Risk Adjustment: National Core Indicators

The National Core Indicator Survey includes a process of outcome or risk adjustment to control for differences in the individual characteristics of people interviewed across states. The method effectively “levels the playing field” across states. It is necessary to perform this analysis because a state that has a broad eligibility definition (e.g., serves people with autism, brain injury, or other developmental disability) will probably have a sample that looks slightly different from a state that only serves people diagnosed with MR.

Only those items that are likely to be affected by individual characteristics are adjusted; the rest are not adjusted. Items that were found to predict outcomes on the consumer survey include: age, gender, legal status; level of MR label, other diagnosis and primary means of expression, and vision. Items are adjusted using a logistic regression model. This model computes a predicted value if all factors were equal across the samples. For more information, visit:
http://www.hsri.org/docs/786_P6_Consumer2004_final.pdf

In constructing risk adjusted Quality Indicators (QIs) for nursing homes, developers used a more direct approach that took into consideration the end users of the quality indicators – the surveyors, facilities and consumers. This approach allows surveyors and others to see the detail that goes into constructing the index (the numerator and denominator, for example) and provides a way to tie a resident- level report to the construction of the quality indicator. (Zimmerman, Karon, Arling et al., 1995).

Risk Adjustment: Nursing Home Indicators

A number of the NF quality indicators are risk adjusted. The indicators include three measures: an unadjusted indicator, a high risk and a low risk indicator. For example, one unadjusted quality indicator is the prevalence of bladder or bowel incontinence. This indicator is further divided into those who are high risk of bladder or bowel incontinence and those who are not. For the high risk quality indicator, the denominator includes all those people who are considered at high risk for bladder or bowel incontinence (e.g., have severe cognitive impairment or are totally dependent in mobility.) The denominator of the low risk QI includes all those people in the nursing facility who do not have a risk for bladder or bowel incontinence.

Risk Adjustment: OASIS Home Health Indicators

For purposes of the OBQI indicators that are being developed for home health agencies, a different approach was taken to adjust for risk. The OBQI indicators are adjusted for risk using a logistic regression technique. This involves developing a predictive formula for a specific outcome using a reference group of patients. The predictive model is applied to obtain an expected agency-level outcome rate, which is then compared to the agency's actual outcome to determine whether care was superior or inferior relative to the reference sample. This provides a way to take into account the patient characteristics and risk factors most closely associated with the specific outcome. Each outcome measure in the OBQI System has its own risk model and this risk model is re-estimated each time outcome reports are produced which means that the current characteristics of the reference sample are always considered (Centers for Medicare and Medicaid Services, 2002).

Population Comparisons

It is not always feasible to develop measures that are risk adjusted. At the same time, there is growing interest in comparing the use, cost and outcomes of services provided to different groups of people who receive home and community based services (e.g. older adults; adults with physical disabilities; adults with MR/DD). When it is not possible to “control” for differences in the characteristics of the comparison groups, it is appropriate to acknowledge these differences in the text or notes to the reader. Any additional information about the characteristics of the groups will also help the reader understand and interpret the data that is presented.

Small Numbers

Data generated from small numbers (either small sample sizes, anecdotal information, or small numbers of reports) can be useful to spot issues or trends but should be reported and interpreted with caution. Looking at trends associated with rare events or small numbers of records should be done with care and adequate documentation of the source and size of the total data base or population should be included.

Statistical Significance

The term, statistical significance, or even “significance” has a specific meaning and implies the use of hypothesis testing and use of statistical techniques. Be careful to use this term only when the appropriate statistical methods have been used. (Program Development and Evaluation, 2002)

Ways to Use or Interpret Data

When developing quality indicator or performance reports, there may be a tendency or desire to draw conclusions about the overall “quality” or “performance” of a system, entity or provider. As indicated previously, a number of factors influence the reliability and validity of any “performance measures,” including the statistical sampling methods used, the source and quality of the data, and methods used to test the measures.

The results of various forms of data analysis, including the preliminary construction of measures, can be used for a variety of purposes that may range from establishment of baseline data for education purposes to the creation of benchmarks for performance based contracts. Some possible uses and ways to interpret results are:

- to establish baseline information;
- to identify areas for further inquiry;
- to identify areas for focused quality improvement; and
- to measure program or system performance

Establish Baseline Information and Educate Stakeholders

When data are aggregated and reported for the first time, the primary purpose of the data report may be to create baseline information for educational and informational purposes. At this stage, it may be difficult to know how to interpret any results absent a trend line or a benchmark for comparison. Nevertheless, the data usually provides a starting point for discussion and way to map progress. The results can also provide a useful educational tool for providers or other stakeholders. It may also provide an initial direction for focusing QA/QI activities.

Identify Areas for Further Inquiry

Oftentimes, when data are first reported, the results may raise more questions than they answer. It is not uncommon for people to criticize or question the accuracy of the data when it is first reported. At this point, the data can be used as a way to identify areas for further inquiry or to guide a more focused data collection process.

As an example, the following table shows the hypothetical rates of emergency room use in an elderly waiver program compared with residents in nursing homes.

Percentage of people with at least 1 Emergency room visit (Year 2000)	
Older Adults Waiver (n=700)	50%
NF Residents (n=5000))	30%

While these numbers begin to tell a story, they do not necessarily point to a particular action. Instead they bring to mind a number of additional questions that would help in understanding the use of emergency rooms by waiver participants. At this point, it may be helpful to bring a mix of professionals (physicians, case coordinators, workers) to discuss these results and brain storm some further analysis.

Some of the follow-up questions might include: what are the most common reasons for emergency room visits; what is the average number of emergency room visits; what is the average number of emergency room visits for those who had at least one visit; did the visits result in an inpatient admission; do the rates vary by geographic area; what control, influence does a waiver program have on emergency room use; what are the trends over time. The first set of analysis suggests a number of follow-up questions and provides the basis for proceeding to the next level of inquiry.

Identify Areas for Focused Quality Improvement

In other instances, the results of a data analysis might point to areas where there is a need for a focused quality improvement effort even if the analysis is not “conclusive” or “statistically significant”. The results of consumer surveys, for example, can be used to identify areas for quality improvement. States that use the national core indicator survey are able to compare the results in their state with national benchmarks. This provides a way to identify areas where a state may want to focus its quality improvement activities. While there are no standards or optimal indicators generated from consumer survey results, they provide useful program information and guidance.

Establish Performance Standards

As states become more confident of the reliability and validity of their data and the appropriate construction of their “measures”, it will be possible to develop preliminary benchmarks for program performance. Universal and standardized measures will be necessary. Nursing home quality indicators are used by program managers to “flag” facilities that are within certain percentile groups. This provides a way to focus provider reviews on facilities that have “outlier” indicators. Some states have begun to use the results of consumer surveys to establish goals for their contractors. Even before performance standards are developed, quality “indicators” can be developed and used to monitor overall performance of a system.

Summary

Developing procedures for testing and monitoring the quality of the data that is used to develop management reports, legislative reports or performance monitoring reports is an often overlooked yet critical function. Accurate and reliable data are necessary to assure that managers, policy makers and the general public have confidence in the reports that are produced and the conclusions that are drawn about the performance of any system.

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