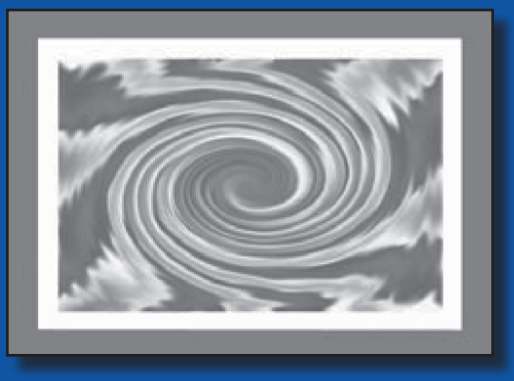

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A Survey Data Quality Strategy: The Institutional Research Perspective

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Association for Institutional Research

Supporting quality data and decisions for higher education.

Abstract

This discussion constructs a survey data quality strategy for institutional researchers in higher education in light of total survey error theory. It starts with describing the characteristics of institutional research and identifying the gaps in literature regarding survey data quality issues in institutional research and then introduces the quality perspective of a survey process and the major components of total survey error. A proposed strategy for inspecting survey data quality is presented on the basis of five types of survey error and the characteristics of typical institutional research survey projects. The strategy consists of identifying *quality measures* for each type of survey error, and then identifying *quality control* and *quality assurance* procedures for each of the quality measures. The discussion concludes with the implications of the strategy for institutional researchers and some closing thoughts. A checklist for inspecting survey data quality is provided in the appendix.

Since the 1960s, institutional research (IR) has emerged as a profession and gradually become an organizational function of higher education institutions in many parts of the world. Its presence in higher education is a response to changing demands of society for its institutions, such as calls for increased accountability and efficiency (McLaughlin & Howard, 2004). Initially, IR appeared as a decentralized set of activities conducted in various offices throughout university/college campuses; however, its function frequently has become centralized in institutional research offices.

Institutional research helps answer three questions essential to the sustained development of an organization: Where is

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the organization at this moment? Where is the organization going? And how can the organization best arrive at its desired end? (Middaugh, Trusheim, & Bauer, 1994, p.1). Institutional research fosters organizational learning (Leimer, 2009), and IR has increasingly become a core administrative function through its integration into the strategic planning and assessment processes of the institution (Morest, 2009). It is anticipated that institutional researchers will not only continue to fulfill their core function by converting data into information but will also become change agents by actively engaging in the process of managing and leading institutional change (Swing, 2009).

What is institutional research about? In his seminal monograph on institutional research, Saupe (1990) defines institutional research as "research conducted within an institution of higher education to provide information which supports institutional planning, policy formation and decision making" (p. 1). As such, the main product of institutional research is information. According to Middaugh et al. (1994), there are multiple institutional research measures including those related to organizational inputs (e.g., students, faculty and staff, facilities, and revenues), processes (e.g., academic programs, program completion, quality, productivity, and strategic planning), outputs (e.g., graduates and student outcomes) and the external environment (e.g., financial considerations, employment market, government concerns, and regional accreditation). The task of institutional researchers involves converting complex data to actionable information (Anderson, Milner, & Foley, 2008) and concerns three interdependent forms of "organizational intelligence" (Fincher, 1985): technical/analytical intelligence, issues intelligence, and contextual intelligence (Terenzini, 1993). Institutional research draws from various methodologies including applied research, program evaluation, policy analysis, and action research, depending on questions it needs to address (Saupe, 1990).

Institutional research distinguishes itself from higher education research in that institutional researchers are more concerned about knowledge about a specific institution or system of institutions whereas higher education researchers are more interested in advancement of theory and practice in higher education in general (Saupe, 1990; Terenzini, 1993). Another difference is the importance of the utilization or application of the information produced through institutional research. The use of information is viewed as an essential component in the *life cycle* of an institutional research activity. Along with other stages of design, collection, preparation, analysis, and dissemination, application of the research results and feedback received are the "primary determinant[s] of success" (Borden, Massa, & Milam, 2001, p. 200).

Institutional research involves three data sources: institutional information systems or administrative data (e.g., student enrollment data or faculty data), external data sources (regional or national data, e.g., Integrated Postsecondary Education Data System in the United States), and data collected as responses to various surveys and queries (Borden et al., 2001). Frequently, the survey used will be a locally developed one. Although a locally prepared survey may be the best option for obtaining the needed information, information users in higher education institutions generally have higher levels of trust in research derived from administrative data than that derived from survey data. A similar pattern is also found among higher education researchers and policy makers, who traditionally have less confidence in softer and more subjective measures such as survey data based on perceptions (Gonyea, 2005). At the same time, more than ever, the demands for external assessment and internal assessment have fueled an increase in the demand for quality survey data (Porter, 2004). Further, the validity of commonly used college student surveys has been called into question and more rigorous and diligent efforts in survey design and evaluation are in demand (Porter, 2011). To increase the acceptance and use of survey data, further efforts are required to improve survey data quality in both higher education research and institutional research.

Unfortunately, literature that examines survey data quality issues in a *holistic* way for the purposes of institutional research professionals is limited.

There seem to be two gaps in the existing efforts to improve on survey methodology. First, while there is a large amount of literature addressing various aspects of a survey project (Croninger & Douglas, 2005; Gonyea, 2005; Porter, 2004; Presser et al., 2004; Sanchez, 1992; Thomas, Heck, & Bauer, 2005), there is lack of synthesis of this literature into a conceptual model for the purposes of quality control. Because of this lack of synthesis, issues of survey methodology have yet to be approached from a survey quality perspective. Because survey quality is a complex issue with multiple dimensions, a lack of synthesis may be understandable without a conceptual model of survey quality. When one particular area is addressed in depth, it is hard to cover other areas and cover the breadth of the topic. However, this synthesis of knowledge is necessary for any kind of survey project if the researcher is serious about the survey data quality, regardless of whether the research concerns multi-institutional surveys such as the National Survey of Student Engagement (NSSE) or in-house surveys specific to one institution.

The second gap, and a related issue, is the lack of a comprehensive conceptual model of survey errors in the field of institutional research. While "serious" institutional researchers are making efforts to improve survey data quality, they often do not rely on any theories on survey methodology (Gonyea, Korkmaz, BrckaLorenz, & Miller, 2010). A survey methodology theory—*total survey error,* to be described later in this paper—is a very helpful way to address survey data quality issues. However, not much can be found in the current institutional research literature in reference to total survey error theory and its applications in institutional research. Although in a few publications, survey issues in the field of institutional research have been approached from the point of view of survey errors (Umbach, 2004, 2005), discourse of data quality is limited. As such, it is meaningful to look at survey issues in institutional research from the perspective of data quality through the lens of a total survey error theory as it provides a theoretical framework for optimizing surveys (Biemer, 2010) and the central organizing structure for survey methodology (Groves & Lyberg, 2010). Such a view informs the following discussion, which aims to incorporate the total survey error paradigm into the survey data quality issues in institutional research.

This task is more pressing given the unbalanced efforts among institutional researchers to improve the quality of data with which they are working. How institutional research provides information support to a higher education institution is illustrated in a book that carries much weight in the field of institutional research, *People, Processes, and Managing Data* (McLaughlin & Howard, 2004). The book presents an information support cycle that involves three stakeholders through five stages of information management: the custodian/supplier (focusing on integrity of the data), the broker/producer (transforming the data into information), and the manager/user (taking the information and applying it to the situation); the center of this information support cycle is quality decision-making (Figure 1). The institutional research function is identified as being mostly aligned to the information broker role while relating to the data custodian and the data user (p. 17). The book, however, only speaks to one of the data sources used for institutional research—administrative data in an institution—and does not address data that are generated from survey research projects. So, the question remains unclear as to how the institutional research function fits into the information support cycle when survey data are involved.

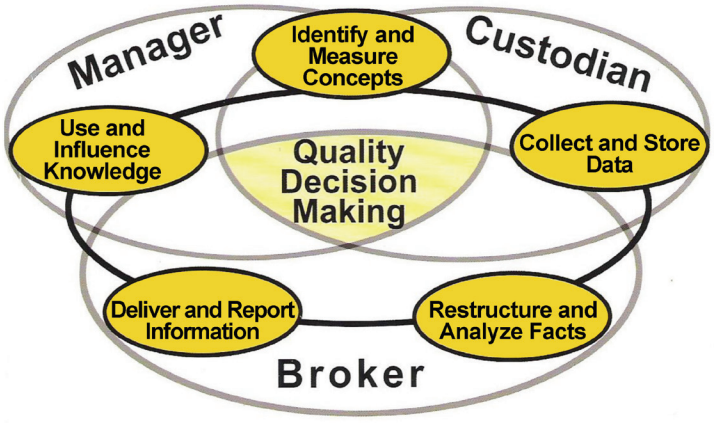

Figure 1. Information support cycle in institutional research.
(Source: McLaughlin & Howard, 2004)

In this context, this following discussion draws upon the total survey error theory and presents a survey data quality strategy for the purposes of institutional research. In the following section, I briefly introduce the quality perspective of a survey process and the major components of total survey error. Then, I present the proposed strategy for survey data quality in a summary table with explanations to follow, and I end with discussions about the implications of the strategy for institutional researchers. It should be noted that the intention is to focus on the big picture and the breadth of survey quality data issues in institutional research, rather than the depth of each issue. Readers interested in a particular topic are encouraged to consult articles addressing individual issues for details.

The *Quality* Perspective of a Survey Process and the Total Survey Error

Doing a survey can be viewed in two ways. First, it can be viewed from a *process perspective*, wherein one might examine all the steps and decisions that are required in a survey project, including determining research objectives based on information needs, determining sampling methods, developing the survey instrument, administering the survey, conducting data analysis, and finally producing the survey report (Alreck & Settle, 1985; Biemer & Lyberg, 2003). This approach describes the survey process as a procedure that is mostly sequential but with iterations.

The second approach to a survey process is to view it from a *quality perspective*. This approach does not focus on how best to implement each step in a survey process but concentrates on what problems may occur in each step and how to overcome or minimize the occurrence of those problems (Groves et al., 2009). In other words, it intends to examine errors that may occur in the survey process with a view of minimizing those errors, thereby improving survey data quality. As such, the *quality* perspective is linked with survey errors, and this is where the concept of *total survey error* comes in. The goal of an optimal survey design is simply stated as "minimizing the total survey error subject to costs and timeliness constraints" (Biemer, 2010, p. 821).

How the *quality* perspective of a survey process compares with the *process* perspective is shown in Figure 2. The quality perspective of a survey process consists of a measurement track and a representation track (Groves et al., 2009), and both tracks move from the abstract to the concrete. The measurement track starts with the *construct,* and the representation track begins with *target population.* As a survey project proceeds from *information needs* to *data processing* and *report generation* from the survey process point of view (Alreck & Settle, 1985), the two tracks move down and converge at the point of obtaining *survey statistics.*

Total survey error is "the difference between a population mean, total or other population parameter, and the estimate of the parameter based on the sample survey (or census)" (Biemer & Lyberg, 2003, p. 36). Survey errors can be organized in different ways. Some categorize them into sampling error and nonsampling error (Biemer & Lyberg, 2003); others classify them into observational error associated with the measurement process (starting with a construct and ending with an edited response) and nonobservational error associated with the representation process (starting with target population and ending with postsurvey adjustments; Groves et al., 2009). Regardless how survey errors are organized (Biemer & Lyberg, 2003; Groves et al., 2009; Weisberg, 2005), the total survey error consists of the following five types of survey error: measurement error, coverage error, sampling error, nonresponse error, and postsurvey (i.e., data processing or adjustment) error. These types of errors are shown in Figure 2 and are described in more detail later.

Each type of survey error creates the risk of variable errors and systematic errors[1], which can

[1] The value of a question item for a particular person is either higher or lower than the true value of the person; the cumulative effects of all errors are positive for some respondents and negative for others. When the variable negative errors in the sample observations tend to cancel the positive errors, these errors are called *variable errors.* Errors that do not sum to zero when the sample observations are averaged are referred to as *systematic errors* (Biemer & Lyberg, 2003, pp. 46–47).

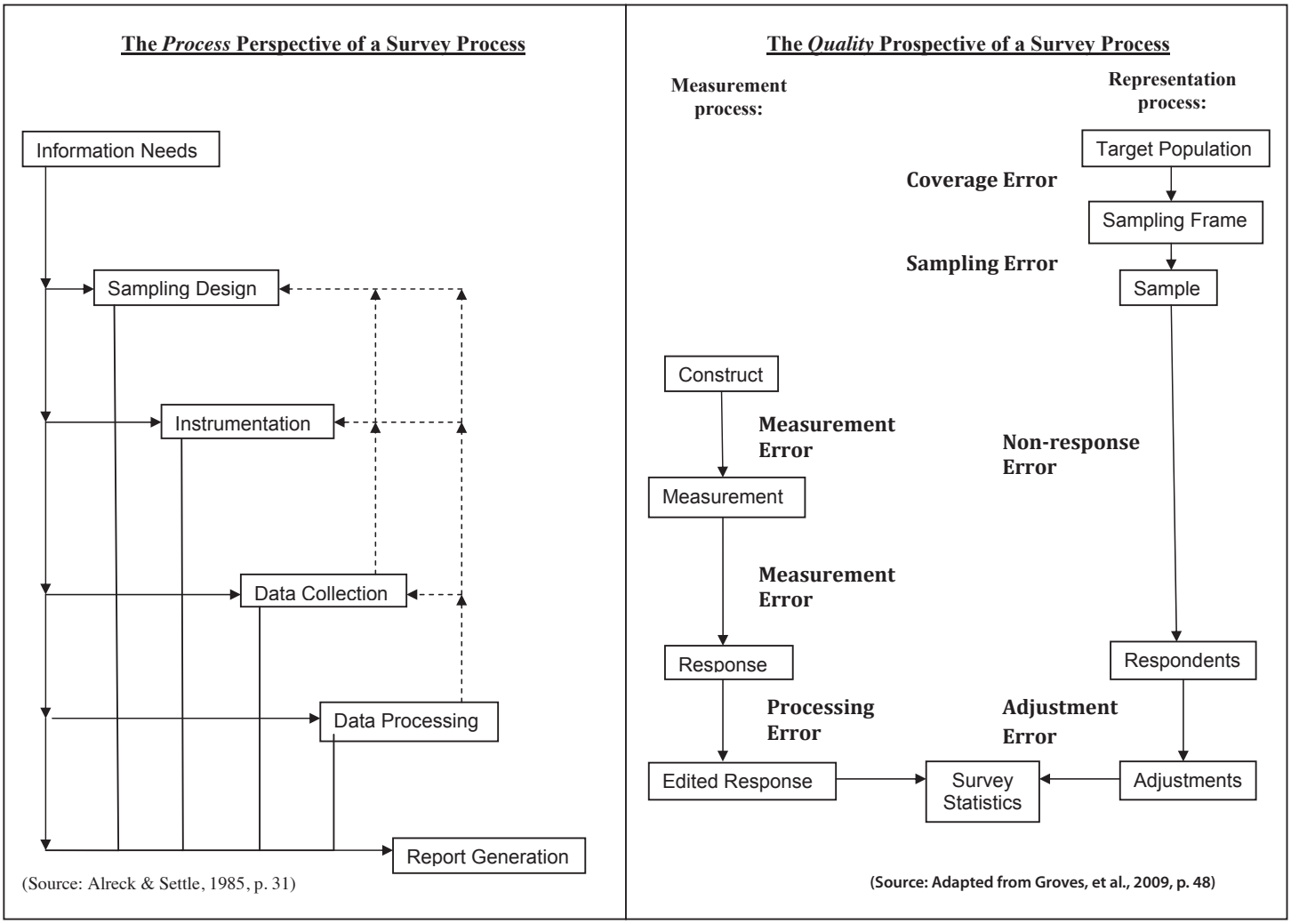

Figure 2. Comparison between the Process Perspective and the Quality Perspective of a Survey Process

Table 1

Risk of Variable and Systematic Errors by Major Error Source in the Institutional Research Context

Types of Survey Error	Risk of Variable Error	Risk of Systematic Error
Measurement error	High	High
Coverage error	Low	Low
Sampling error	High	Low
Non-response error	Low	High
Post-survey/Data processing error	High	Low

Note. Modified from *Introduction to Survey Quality* (p. 59), by P. P. Biemer and L. E. Lyberg, 2003, Hoboken, NJ: John Wiley & Sons, Inc.

result in error variance and bias[2] respectively. Error variance and bias are two measures of data quality, with variance being easier to measure and control than bias (Bailar, Herriot, & Passel, 1982; Czaja & Blair, 2005). Table 1 identifies the risks of variable error and systematic error for the five types of survey errors.

In general, among the five types of survey error, the sampling error is subject to a low risk of systematic errors whereas the other four types likely have a high risk of systematic errors (Biemer & Lyberg, 2003, p. 59). This is because in a typical survey using reasonable sampling methods, the risk of systematic error from the sampling error is quite small, while the risk of variable error is inevitable. In contrast, the risk of systematic error from the measurement error is high as a questionnaire may be poorly designed. The risk of systematic error from the coverage error is high as a group of people may be completely missing from the sampling frame.

In a typical institutional research survey project, the target population is generally either students or faculty/staff members of the institution, which is usually a finite population. The sampling frame is usually available from the student information system or the human resources database, and this advantage has reduced the risk of the systematic error from coverage error. The target population usually uses emails and online resources regularly. This has made it easier to administer web surveys to university/college students or faculty/staff than the population outside this context, and has made web surveys a commonly used survey mode within higher education institutions. Furthermore, higher education institutions usually have access to relatively advanced data entry and processing resources (e.g., software and research expertise), which may help reduce data processing errors. Given these characteristics, the risk of variable errors and the risk of systematic errors in each type of survey error may be different from those in a survey project in other contexts. Table 1 shows an indication of the risk of variable and systematic errors in the five types of survey error in a typical institutional research survey project.

Survey Data Quality Strategy

The survey data quality strategy proposed in this paper addresses the five identified types of survey error in a framework of quality assurance and quality control in surveys (Lyberg & Biemer, 2008).

There is a fine distinction between the two concepts: "Quality assurance ensures that processes are capable of delivering good products, while quality control ensures that the product actually is good" (Lyberg & Biemer, 2008, p. 426). As such, quality assurance is related to the survey process while quality control is associated with the survey product. Therefore, survey researchers are pursuing both *process quality* and *product quality*. Survey quality is assured by using dependable processes (process quality), and these processes lead to good product characteristics (product quality) (Biemer & Lyberg, 2003). In light of this framework, the characteristics of quality survey data that have been collected (i.e., the product) need to be defined for the purposes of quality control, and the characteristics of a quality survey process should be identified for the purpose of quality assurance.

With these considerations in mind, three components comprise the proposed survey data quality strategy: *quality measures*, which are the characteristics or indicators of quality survey data; *quality control procedures*, which are used to inspect the various aspects of the survey and the data and to examine whether the aspects and obtained data have those characteristics of quality, as specified by the quality measures; and *quality assurance procedures*, which are used to inspect the survey process and check whether certain procedures were implemented during the survey process to ensure that the resulting survey data set will have those characteristics of quality survey data, as specified by the quality measures.

[2] *Variance* means the differences manifested in repeated trials of a procedure, and reflects the degree of spread or variation in a sample. *Bias* is an estimate that is consistently higher or lower than the true population value (Czaja & Blair, 2005).

In Table 2, the survey data quality strategy is presented in a matrix with the five types of survey error as rows, and the three areas of quality inspection as columns. The strategy is also aligned with the two approaches to addressing the issue of survey errors: error measurement and error reduction (Czaja & Blair, 2005). The quality control procedures are aimed to measure and assess survey errors, and the quality assurance procedures are intended to reduce survey errors.

The following sections identify the quality measures for each of the five types of survey error and elaborate on the corresponding quality control and quality assurance procedures in the context of institutional research. Table 2 serves as a summary of these measures and their related procedures.

Quality Inspection for Measurement Error

Measurement error occurs when there are differences between the responses obtained and what was to be measured. In reference to Figure 2, measurement error represents the gap between the *construct* and the *measurement,* and the gap between the *measurement* and the *response;* these gaps may occur in the processes of *instrumentation* and *data collection*. Relating to the measurement error, quality survey data are characterized by three indicators: reasonably good validity, reasonably good reliability, and minimized response bias.

Quality control procedures. As the *sine qua non* of measurement, *validity* is the extent to which the survey measure actually reflects the intended construct.[3] Assessing validity is mainly considered to inspect correlations.[4] As construct validity subsumes content and criterion-related validity (Borden & Young, 2008), it has become an overarching concept when thinking about validity. When the measurement is consistent with the theoretical concept behind it, then the data have construct validity. Construct validity has two measures: convergent validity (measured by a positive correlation between the survey responses with responses to similar questions in other surveys) and discriminant validity (measured by a relatively low correlation between the survey responses and answers to other questions that measure a different construct). While the multitrait-multimethod matrix has been recommended to assess the convergent and discriminant validity (Campbell & Fiske, 1959), actually implementing it may be too monumental a task for institutional researchers. However, its implications on performing triangulation to assess the construct of interest still apply. This means that institutional researchers should inspect question items using different observation techniques in order to verify that the question items actually measure the same concept or the construct. Factor analysis is a statistical technique that is helpful for inspecting construct validity (Comrey & Lee, 1992; Gregory, 2004).

Reliability is "a measurement of the variability of answers over repeated conceptual trials" (Groves et al., 2009, p. 281). It addresses the question of whether respondents are consistent or stable in their answers, and it is therefore also known as *response variance* (Groves et al., 2009). Reliability is often computed as the correlation of two survey estimates, and reliability in the responses can be assessed in three ways: internal consistency (typically measured by Cronbach's alpha), split-half reliability, and test-retest reliability (both typically computed by Spearman-Brown coefficient). For qualitative responses, there is also inter-rater reliability to assess the reliability of the scoring.

Response bias is a systematic deviation or discrepancy between the sample estimate and the true population parameter; in other words,

[3] I acknowledge the myriad types of validity and also recognize the evolving concept of validity (Borden & Young, 2008). As my discussion in this section is concerned with measurement issues in survey data, I focus on validity only as the *sine qua non* of measurement.

[4] Other approaches to validity may be used to examine validity issues. For example, Porter (2011) has used an argument-approach to validity.

Table 2

Summary of the Major Components in the Survey Data Quality Strategy

Types of error	Quality Measures (Indicators of Quality Data)	Quality Control Procedures (inspecting the survey data to *measure* errors)	Quality Assurance Procedures (inspecting the survey process to *reduce* errors)
Measurement error	Reasonably good validity Reasonably good reliability Minimized response bias	Assess validity by checking construct validity (e.g., factor analysis), concurrent validity, and divergent validity. Assess reliability by checking internal consistency, split-half reliability, test-retest reliability. Assess response bias by o Comparing survey data with data or information from other sources; o Checking occurrence of response tendencies.	Construct a good questionnaire. Conduct cognitive interviews. Ensure adequate respondent behavior. Ensure adequate interviewer behavior (if interviewer-administered).
Coverage error	Minimized discrepancy between the sampling frame and the target population	Check whether there exist undercoverage cases, ineligible units, or duplications in the sampling frame. Compare the specifications of the target population and the corresponding parameters of the sampling frame.	Develop a working definition and clearly defined specifications of the target population. Locate a readily available list that includes as many elements of the target population as possible.
Sampling error	Sample representativeness Reasonable margin of error	Compare the distributions of obtained sample with those of the sampling frame by certain demographic characteristics. Make sure that the margin of error is below 5% for expected number of respondents at the 95% confidence level.	Appropriate implementation of a sampling procedure. Calculate a reasonable sample size based on the size of the sampling frame, the expected margin of error, analysis need for data breakdown, the anticipated response rate, and the resources available for the survey.
Non-response error	At the unit level: o A reasonable response rate; o Insignificant difference between respondents and non-respondents.	Calculate the response rate: Response rate = C/(C+NC+R+O) or C/(S-NC) (C=completed questionnaires; NC=non-contacts; R=refusals; O=other non-respondents; S=sampled survey recipients) Assess the difference between the respondents and the non-respondents by: o Assessing the level of interactions of non-response with the topics; o Comparing the demographic characteristics of the survey respondents with those of the sampling frame; o Examining the characteristics of the late respondents.	Use techniques in the process of questionnaire design and survey administration to combat: o Non-contacts; o Refusal; o Inability to participate.
	At the item level: o A reasonable proportion of missing data in responses to each question item; o Insignificant difference between respondents and non-respondents to each question item.	Do item non-response analysis by o Calculating the proportion of missing data for each question; o Deciding whether the data are missing completely at random; o Investigating variables with a large proportion of missing data.	
Post-survey error	Correctness in processing individual cases and aggregate data	Rely more on expertise and professional morale of individual researchers	Carefully perform the procedures of o Data cleaning; o Data adjustment; o Data analysis.

the respondent mean response is consistently higher or lower than the true mean score of the population. Response bias can come from sources such as mood, social desirability, language difficulty, extreme-response sets, and acquiescence (Crano & Brewer, 2002, pp. 54–55).

There are two ways to assess response bias. One is to compare survey data with data or information from sources external to the survey. An example of this method is to check with the stakeholder or the sponsor of the survey project to find out whether the survey findings about a particular question are far different from their experience or knowledge. Another way of assessment is to evaluate the occurrence of certain response tendencies, such as respondents giving socially acceptable answers, avoiding using the extreme response categories of a rating scale, or giving the same answer to all alternatives in a rating scale (known as *strong satisficing;* Groves et al., 2009).

Quality assurance procedures. Measurement error can be reduced through the following techniques. First, researchers should construct a good survey that is based on a well-supported theory or conceptual framework, and work to have high quality question wording and questionnaire structure. As an institutional research survey project is often initiated by certain institutional needs, the survey instrument tends to be constructed mainly from experience and less often from a literature-based conceptual framework. However, despite the applied nature of an institutional research project, a literature review should be part of the survey design process.

Second, cognitive interviews should be conducted to ensure the target population understands the questions in the same way as the questionnaire was intended.

Third, adequate respondent behavior involves optimal completion of the cognitive process and sufficient motivation on the part of the respondent; therefore, the questionnaire should be designed and administered with a view to ensuring participants actually go through the four components of the mental processing in answering survey questions: comprehension, retrieval, judgment, and response (Tourangeau, Rips, & Rasinski, 2000). An example of failing to do so is strong satisficing, which may occur when respondents skip the retrieval and judgment steps and proceed to the response step (Groves et al., 2009). Questions can be asked regarding how the respondents complete the questionnaire and how they self-evaluate their motivation and ability while answering the questionnaire.

Fourth, for interviewer-administered surveys, procedures should ensure adequate interview behavior, which is measured by low interviewer variance and can be best analyzed with multilevel analysis (Loosveldt, Carton, & Billet, 2004).

Quality Inspection for Coverage Error

In reference to Figure 2, *coverage error* occurs when differences between the sampling frame and the target population exist. Quality survey data are characterized by minimized discrepancy between the sampling frame and the target population.

Quality control procedures. Bias exists when some components in the target population are not available or accessible in the sampling frame. According to Groves et al. (2009), this may be caused by situations where elements in the target population do not, or cannot, appear in the sampling frame (i.e., *undercoverage*), units in the sampling frame are not in the target population (i.e., *ineligible units*), and several units in the frame are mapped onto the single element in the target population (i.e., *duplication*). Therefore, researchers should check for those cases.

Another procedure for assessing the discrepancy between the sampling frame and the target population is to compare the specifications of the target population and the corresponding parameters of the sampling frame. As higher education institutions usually assign their students an institutional email address when they first enroll in their studies, the coverage error is not as big a threat to web surveys in institutional research as it is other fields in general (Couper, 2000). This is increasingly true as institutions use student email addresses in online course management systems.

Quality assurance procedures. Researchers need to develop a working definition and clear specifications of the target population and locate a readily available list that includes as many elements of target population as possible. In the context of institutional research, a typical target population is a student cohort with certain characteristics when they are applying for studies (perspective students), are currently enrolled in certain programs of study (current students), or have graduated within a certain time frame (graduates). A higher education institution usually has a well-established student database, so the sampling frame is often stable, complete, and accessible. Therefore, the risk of variable errors and systematic errors related to coverage error is generally low and more controllable.

Quality Inspection for Sampling Error

Sampling error is the difference between the survey estimate and the population parameter as a result of taking the sample instead of the entire population. In reference to Figure 2, sampling error represents the gap between the *sampling frame* and the *sample.* A good set of survey data is representative of the sampling frame by known demographic parameters. When probability sampling is used, margin of error is a commonly used measurement of the level of random sampling error. The commonly acceptable margin of error is less than 5% at the 95% confidence level.

Quality control procedures. Sample representativeness can be determined by comparing the frequency distributions of the obtained sample and those of the sampling frame by certain demographic characteristics. If the difference in the frequency distributions is negligible, then the obtained sample is considered to represent the sampling frame by those indicators.

Margin of error is affected by variance and sample size: the smaller the variance and the larger the sample size, the smaller the margin of error. For estimating the margin of error for the mean of an interval or ratio variable, we need to know the population standard deviation.[5] For a survey project in institutional research that usually has a finite population, the margin of error for a variable can be calculated on the basis of the total target population and the sample size[6] (Groves et al., 2009).

Quality assurance procedures. The magnitude of sampling error is more controllable than other types of survey errors and, therefore, is considered as intentional error (Biemer & Lyberg, 2003). The sampling error can be controlled by making a good sample selection, which is featured by random selection of elements in the sampling frame and key subgroups of the population being well represented in the sample. Appropriate implementation of a sampling procedure requires four considerations: probability sampling, stratification, clustering, and sample size. Sampling bias can be easily removed by giving all elements an equal chance of selection; sampling variance is reduced when the sample size is big and the sample is stratified and is not clustered (Groves et al., 2009).

An appropriate sampling strategy involves calculating a reasonable sample size. The sample size is determined by the sampling frame, desired margin of error, and anticipated response rate, analysis need for data breakdown, and the resources available for the survey. Table 3 shows an example to illustrate this. Please note that the margins of error presented in the table are calculated for a dichotomous variable using the maximum variance, that is, the standard deviation equaling 0.5 (Groves et al., 2009).

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[5] The formula is: $M = 1.96 * \frac{\sigma}{\sqrt{n}}$ (at the 95% confidence level)
(σ: population standard deviation, usually obtained from literature reviews, expert knowledge, historical data, survey data or pilot studies; n=sample size).

[6] Margin of Error = 1.96 * S $= 1.96 * (\sqrt{1-f} * \frac{s}{\sqrt{n}})$ (for a variable, at the 95% confidence level)
(S: Standard Error; $\sqrt{1-f}$: finite population correction factor, f=n/N; s: variable's standard deviation; n=sample size; N=population)

Table 3

An Example of Determining the Sample Size for an IR Survey Project

Margin of Error (95% confidence level)	Sample Size	Anticipated Response Rate	Survey Invitees
5.57%	300	20%	1500
4.80%	400	20%	2000
4.27%	500	20%	2500
3.88%	600	20%	3000
3.57%	700	20%	3500
3.32%	800	20%	4000
3.12%	900	20%	4500

Note. 1. The sampling frame is 10,000 students.
2. This table is produced with the assistance of an online sample size calculator tool (http://www.raosoft.com/samplesize.html)

With a sampling frame of 10,000 students, if a researcher wants to make sure that the obtained margin of error is below the desired 5%, then the sample size needs to be 400 (margin of error of 4.8%). If a response rate of 20% is anticipated, then a total of 2,000 students need to be invited to participate in the survey. If the 400 obtained sample is going to be broken down into subgroups for data analysis purposes, for example, for an institution with eight schools or faculties, then in each subgroup, there are 50 respondents. This size of respondents is acceptable for descriptive statistical analysis. However, if the researcher intends to conduct inferential statistical analysis or multivariate data analysis, s/he may want to consider increasing the sample size to 800 (the number depends on the questions to be answered), which results in a margin of error of 3.32% and a sample size of 4,000 when the anticipated response rate remains 20%. If the survey project is going to be administered in the web mode, the increased number of survey invitees will not matter because the bigger size will not add much to the total survey costs; however, when the mail survey is used, the increased costs from questionnaire distribution and data entry and processing will be a consideration in determining sample size. All these considerations will need to be balanced. Using an online calculation tool (e.g., http://www.raosoft.com/samplesize.html) can facilitate the process of computing the margin of error and the sample size when using dichotomous variables.

Quality Inspection for Nonresponse Error

In reference to Figure 2, *nonresponse error* represents the gap between the *sample* and the *respondents*. This error occurs when some people from the sample who were invited to participate in the survey do not respond to the survey request or fail to respond to some of the questions in the survey. Therefore, there are two types of nonresponse error: *nonresponses at the unit level* and *nonresponses at the question item level* (Biemer & Lyberg, 2003; Groves et al., 2009; Weisberg, 2005). *Nonresponse bias* occurs when the statistics computed from respondent data differ systematically from those based on the entire sample data in terms of known characteristics of interest.

Quality control procedures for unit nonresponses. The measurement of nonresponse bias is the function of the nonresponse rate and the difference between the respondent and

nonrespondent estimates (Biemer & Lyberg, 2003). As the nonresponse rate is the proportion of eligible survey recipients who did not respond to the survey, it can be calculated from the response rate. As such, a quality survey data set is characterized by a reasonable response rate and insignificant difference between respondents and nonrespondents with regard to the characteristics of interest to the survey.

The difficulty in calculating the response rate usually lies in computing its denominator. For a survey project in institutional research, when the sampling frame is carefully extracted according to a well-defined target population, the response rate can be calculated in two primary ways: one is C/(C+NC+R+O), where C=completed questionnaires, NC=noncontacts, R=refusals, and O=other nonrespondents (e.g., those who cannot understand due to language problems); the other is simply C/(S-NC), where C=completed questionnaires, S=sampled survey recipients, and NC=noncontacts. It can be seen from the two formulae that the sampled survey recipients actually consist of the survey respondents and three groups of nonrespondents (i.e., noncontacts, refusals, and other types of nonrespondents).

Three methods can be used to assess the difference between respondents and nonrespondents. First, assess the degree to which nonrespondents will interact with the topics or issues of the survey. Usually, those who are highly involved with the topic of the survey are more likely to respond than those who are not, and those who have neutral opinions about the topic or have less experience are more likely to discard the questionnaire (Alreck & Settle, 1985). For example, when an institution is conducting a survey targeted at its current students to find out how they have used its library services, it is important for the researcher to bear in mind that the obtained responses will over-represent the characteristics of those actual library users since those who have used the library services are more likely to respond to the survey. Therefore, it is erroneous to use the data to draw a conclusion about the library use pattern of all current students. Second, compare survey respondents' demographic characteristics with those of the sampling frame and find out whether the respondents under-represent some subgroups in the sampling frame and whether members of the under-represented groups tend to answer some of the substantive survey questions somewhat differently than others (Czaja & Blair, 2005). Third, examine the characteristics of the late respondents. Those who respond to the very last follow-ups may have similar characteristics to people who never respond, and hence, the responses from late respondents can be used to infer what the nonrespondents' would have answered (Suskie, 1996).

Quality control procedures for item nonresponses. Similar to unit nonresponse error, item nonresponse error is a function of the item nonresponse rate and the difference between item respondents and nonrespondents. Item nonresponse results in missing data. Hence, there are two characteristics of a quality survey data set at the question item level: a reasonable proportion of missing data for responses to each question item, and an insignificant difference between respondents and nonrespondents to each question item.

Investigation into missing data and the difference between item respondents and nonrespondents involves item nonresponse analysis. A relatively large proportion of missing data for certain question items should be reported as a red flag for further investigation. Item nonresponse analysis involves examining (a) whether nonresponse occurrence is related to certain demographic characteristics of the respondents, or in other words, whether a particular group of respondents tends to fall short of substantial responses than others, and (b) whether the nonresponses to various question items are related.

Item nonresponse analysis can be conducted in three ways: (a) calculate the proportion of missing data for each question; (b) decide the characteristics of missing data: missing completely at random, missing at random, or missing not at random (Allison, 2002); and (c) investigate variables with a

large proportion of missing data, and find out what may be the causes.

Quality assurance procedures for nonresponses. Quality assurance procedures are derived from three types of unit nonresponse: noncontacts (failure to reach the survey recipients), refusals (recipients' decline of the survey request), and recipients' inability to participate (because of sickness, unavailability, language barriers, etc.; Biemer & Lyberg, 2003; Groves et al., 2009). The third situation also applies to item nonresponse; that is, some recipients may not be able to answer some of the questions because they find the questions difficult to understand, or they cannot retrieve requested information from memory, or the questions are beyond their capacity to answer. Survey nonresponse has been increasing, and much of the nonresponse is due to rising rates of refusals. A particular problem for institutional research survey projects is multiple surveys of students and the resulting survey fatigue (Porter, Whitcomb, & Weitzer, 2004).

The reasons for nonresponses can be due to the social environment (e.g., survey fatigue), can be demographically related (e.g., male students may be less likely to respond to a survey request than females), and can be concerned with questionnaire design and survey administration. The factors related to survey design are more controllable than social or personal factors.

Various techniques can be used to reduce the three types of nonresponse from survey design points of view (Czaja & Blair, 2005; Groves et al., 2009; Porter, 2004). Examples for reducing noncontacts are obtaining accurate contact information of the sampled recipients, and creating email messages that are not flagged by spam filters when using web surveys. Effective methods to combat refusals are notification about the survey prior to its launch, courteous initial contact messages (letter or email), the manner of requesting participation (e.g., the tone of the request, the signature, salience, and ensured confidentiality), a reasonable number of reminders, the appropriate timing of data collection, and the use of incentives. To help with the ability to participate, the survey instrument should be in reasonable length, be easy to read, and ask for relevant, available, or accessible information rather than inestimable information (Groves et al., 2009). A survey-friendly environment will also be helpful for increasing responses. Survey recipients are generally more likely to respond when a survey coordination mechanism is in place so that survey fatigue can be mitigated, and when it is known that survey results have been acted upon.

Quality Inspection for Postsurvey Error

Reliable findings and valid conclusions rely on correct data processing procedures for both individual data and aggregate data. *Postsurvey error* refers to all the errors that occur in the data processing process after the survey data are collected. In this data processing process, raw data are being transformed into information represented by survey statistics. As shown in Figure 2, the postsurvey errors occur when a *response* is turned into an *edited response* on the measurement track, and when adjustments are made to the *respondents* on the representation track, and when the edited or adjusted responses are converted into *survey statistics*.

Quality control and assurance procedures. Various data processing activities after data collection can be organized into three types of procedure: data cleaning, data adjustment, and data analysis. Data cleaning involves inspecting accuracy of data entry, and checking for outliers and inconsistent data. Data adjustment involves considerations of using weights, handling missing data, and creating composite variables when needed. Data analysis involves conducting reliability and validity analysis, inspecting assumptions, choosing appropriate statistical techniques, and conducting statistical computing. When open-ended questions are used, coding is required, and involves inspecting weaknesses in coding structure and coder variance. It is usually hard to quantify how accurate and appropriate these procedures are while the researcher conducts data cleaning, data adjustment, and data analysis. Unlike the other types of survey errors, all these steps are in a researcher's control. Therefore,

whether each procedure is implemented correctly and appropriately relies, to a large extent, on the researcher's expertise and professional morale (for example, his/her diligence, rigorousness, meticulousness, and perseverance in data processing). Nevertheless, for quality control purposes, the procedures in data cleaning, adjustment, and analysis should be documented in detail to demonstrate evidence for quality in the data processing.

Implications

The survey data quality strategy presented in this paper has two practical implications for institutional researchers.

First, survey data quality requires the use of multiple indicators. Survey data quality is multidimensional. This means that relying on one single indicator to evaluate survey data is a misleading practice, and the myth about the response rate is a good example. Institutional researchers sometimes hear such comments from information users as "With such a low response rate, the survey results are problematic" and "The response rate of the survey is high so the data represent the population well."

The measures and procedures in the survey data quality strategy (see Table 2) suggest that a reasonably high response rate is simply one of the indicators for quality survey data though a very important one. To assess unit nonresponse error, the researcher also needs to consider whether there is any difference between responses and nonresponses in characteristics of interest. In evaluation of the quality of a survey data set, quality indicators derived from other types of survey error, such as any response bias that may affect the measurement error, and sample representativeness and margin of error to measure the sampling error, need to be included in addition to the response rate. Also, the response rate does not speak to the representativeness of survey responses, which is a separate indicator for nonresponse bias. Therefore, a relatively high response rate *reduces* the risk of nonresponse bias; however, this single indicator does not necessarily lead to the conclusion that the survey data have low nonresponse bias if the nonrespondents are very distinctive on the survey variable (Groves et al., 2009). As such, the strategy helps debunk some myths about survey data quality and encourages researchers to examine other quality indicators while focusing on one indicator such as the response rate.

Second, it is important to document survey data quality. The survey data quality strategy lends more importance to quality documentation. The strategy proceeds from types of survey error based on the theory of total survey error; it consists of quality measures for each type of survey error and identifying quality control and quality assurance procedures that address each of the quality measures. Table 2 provides an organizational outline for deriving evidence of survey data quality and the procedures for collecting the evidence. Therefore, in the final analysis, the task of an institutional researcher is to collect evidence from the characteristics of the obtained survey data and the implemented survey process to convince information users that the survey data that have been collected are good for certain conclusions. The more evidence that is identified and presented, the greater the trust gained from the information users. This evidence collection process requires documentation.

The information about the identified evidence relating to survey data quality is called *metadata* (i.e., data about data). Four types of metadata can be used to document survey data quality (Groves et al., 2009): definitional (investigated constructs, target population, sampling frame, and coding terminology), procedural (data collection procedures), operational (data cleaning, data adjustment, and data analysis procedures), and systems (data set format, file location, retrieval protocol, and codebook).

In the report of an institutional research project, an appendix usually provides a detailed description of the methodology employed in the study (Bers & Seybert, 1999). The appendix is a good place in a survey report to document evidence for survey data quality, and it should be an integral part of the report. A psychometric portfolio is also

recommended for reporting the evidence (Gonyea et al., 2010).

The purpose of documentation is to communicate the characteristics of the survey data set and the procedures employed to obtain quality indicators, so as to build and enhance trust among information users (if there are any) in survey findings and help them interpret the findings in an appropriate way. Based on the elements in the survey data quality strategy in Table 2, I have developed a checklist (see the Appendix) for institutional researchers to facilitate their documentation efforts.

Concluding Thoughts

This discussion has presented a survey data quality strategy in light of the theory of total survey error for the purpose of institutional research that is conducted in higher education institutions. The strategy consists of indicators of quality data (quality measures) and identifying procedures that are used to inspect the survey data and the survey process (that is, the quality control and quality assurance procedures) so as to measure and reduce errors. The strategy is summarized in Table 2, and the paper elaborates on each of its components; a checklist for institutional researchers is provided in the appendix.

Here are two final thoughts about survey data quality issues. The first is related to how *survey data quality* fits in *survey quality*. As outlined by Lyberg and Biemer (2008, p. 428), *survey quality* is recognized as a three-level concept: product quality (i.e., "the set of product characteristics ideally established with the main users"), process quality (i.e., "a well-designed and tightly-controlled process"), and organizational quality (i.e., "reliable organizational characteristics to ensure that the organization is capable to develop dependable processes that can deliver quality products"). The three levels are interdependent (i.e., organizational quality is required for process quality, and process quality is required for product quality), and all the three levels contribute to quality decision-making.

Survey data quality is actually part of the product quality of a survey and "is achieved through process quality" (Biemer & Lyberg, 2003, p. 24). The survey data quality strategy mainly addresses two of the three levels of survey quality: the product quality and the process quality. Organization quality is more concerned with organizational culture and information management, and involves information infrastructure for quality survey data. It is not addressed in the strategy presented in this discussion.

The second closing thought relates to how survey data quality stands in McLaughlin's and Howard's (2004) information support cycle in institutional research (see Figure 1). When the survey data quality strategy proposed in this paper fits into the information support cycle, the institutional researcher actually takes the bulk of responsibilities in this cycle—the responsibilities of both the custodian and the broker, and implements the larger proportion of the information support cycle—from identifying concepts to delivering a report, while working with the manager. In contrast, when administrative data are used, the institutional researcher usually does not get as involved in the stages of collecting and storing data. Therefore, the role of the researcher is of greater importance in the information support cycle when a survey project is conducted. This may provide another reason for further investigating survey data quality issues and making greater efforts to improve survey data quality in order to better fulfill the information support function of institutional research.

In the context where attention to detail and quality control is recognized as a personal and professional dimension of effectiveness in institutional research (Knight, 2010), it is hoped that this paper contributes to filling a gap in literature of survey quality control for institutional research purposes.

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Appendix

A Checklist for Inspecting Survey Data Quality in an IR Survey Project

Questions to detect measurement error:

- ❑ Did the construction of the survey instrument follow a rigorous design procedure? Were cognitive interviews conducted?
- ❑ Is there any evidence that shows reliability in the survey data?
- ❑ Is there any evidence that shows validity in the survey data?
- ❑ Is there any pattern or tendency in occurrence of the responses?

Questions to detect coverage error:

- ❑ Were the specifications of the target population clearly defined?
- ❑ Did the sampling frame include as many elements of the target population as possible? Did the parameters of the sampling frame correspond with the specifications of the target population?
- ❑ Were there any undercoverage cases, ineligible units or duplications in the sampling frame?

Questions to detect sampling error:

- ❑ Was the sample size reasonable? (How many respondents did you expect to obtain? What margin of error was expected? What response rate was anticipated?)
- ❑ What sampling method was used? Was the method appropriate? Did you give equal chance of selection? For which subgroups did you give unequal chance of selection (if using stratification)?
- ❑ With the number of the respondents and the total target population, what was the margin of error? Was the obtained margin of error reasonable?

Questions to detect non-response error:

- ❑ Was the response rate reasonable?
- ❑ Considering the topic of the survey, who may have been more likely to respond to the survey and who may have been less likely to respond?
- ❑ How did the profile of the respondents compare with that of the target population (or sampling frame) by certain demographic characteristics of interest?
- ❑ How were key subgroups represented in the respondents?
- ❑ Are there any flaws in questionnaire design and/or survey administration that may have resulted in non-responses by some survey recipients?
- ❑ Are there any question items that have a relatively large proportion of missing data? What may have been the causes? Did you report the missing data?

Questions to detect post-survey error:

- ❑ How were the data cleaned? Was the procedure appropriate?
- ❑ How were the data coded? Was the procedure appropriate?
- ❑ How were the data weighted (if applicable)? Was the method correct?
- ❑ How were the data imputed (if applicable)? Was the method appropriate?
- ❑ What statistical techniques were used? Had the assumptions been inspected? Were the statistical procedures properly implemented?

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