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ABSTRACT

To ensure validity in survey research, it is imperative that we properly educate doctoral students on best practices in data quality procedures. A 14-year analysis of 679 studies in the AIS "Basket of 8" journals noted undercommunication in the most pertinent procedures, consistent across journals and time. Given recent calls for improvements in data transparency, scholars must be educated on the importance and methods for ensuring data quality. Thus, to guide the education of doctoral students, we present a "5-C Framework" of data quality procedures derived from a wide-ranging literature review. Additionally, we describe a set of guidelines regarding enacting and communicating data quality procedures in survey research.

Keywords: Doctoral program, IS curriculum, IS research, Data management

1. INTRODUCTION

Jane is a doctoral candidate in her fourth year of the Information Systems Ph.D. program. She collected data for her dissertation via an online survey of 500 full-time employees. Although Jane successfully completed all her statistics and methods courses, opening the survey results gives her pause. Jane knows how to analyze data but doesn't know what to do with the messy data set she's obtained. If she doesn't handle the data correctly, her results could be skewed, and her hard work could have been in vain.

The preceding scenario is not uncommon for doctoral students. While students recognize the need for data quality in survey research, the proper procedures are often not easy to determine. Knowing what to do and when is paramount for any researcher in our field.

Survey research has traditionally been, and is expected to continue to be, one of the primary methods for Information Systems (IS) researchers (Kakhki et al., 2021). According to Wilson et al. (2021), "[s]urvey research will likely continue to have a prominent position in the IS field into the foreseeable future…" (p. 761). Despite its numerous benefits—including

ease of access to subjects and a relatively short time spent in data analysis—difficulties abound in ensuring the quality of obtained data. Surveying human subjects presents challenges due to missing responses, inattentive subjects, skewed results, methodological biases, and more, which pose threats to statistical conclusion validity (DeSimone & Harms, 2017; DeSimone et al., 2015).

In recognition of these threats, the standards expected of survey research have changed in recent years. Numerous calls for increased transparency in our top journals (e.g., Burton-Jones et al., 2021; Kakhki et al., 2021) highlight the need for greater attention to, and communication about, how data quality procedures are enacted before, during, and after survey administration. The bar has been raised for those expecting to publish survey research in IS journals in the years to come.

Along with higher standards comes the need to prepare future researchers with the tools to handle data correctly. Doctoral students represent the future of our field, and as methodological training is central to doctoral education, we must continue to ensure that students are being suitably trained. This training can occur formally through doctoral curricula and informally through exemplars in published research. In this paper, we address both. We perform a data analysis of survey studies published in the AIS "Basket of 8" journals over fourteen years to address our first research question – what is the current state of data quality procedures as communicated in published IS research? Our analysis highlights procedures that, historically, have either not been adequately performed or have not been communicated by IS researchers. Then, informed by a wide-ranging review of survey methodology literature across numerous fields, we address our second research question – what are the best practices on data quality procedures that should be included in doctoral curricula?

2. ANALYSIS OF CURRENT IS LITERATURE

2.1 Procedure

To illustrate the current state of communication of data quality procedures in survey methods in the IS field, we investigated all papers published in the AIS "Basket of 8" journals between 2008-2021. The 8 journals are MIS Quarterly (MISQ), Information Systems Research (ISR), Journal of the Association for Information Systems (JAIS), Journal of Management Information Systems (JMIS), Information Systems Journal (ISJ), Journal of Information Technology (JIT), European Journal of Information Systems (EJIS), and Journal of Strategic Information Systems (JSIS). We performed within-text searches for the terms "survey," "questionnaire," or "panel" to eliminate studies that did not use surveys as any part of their methodology. We excluded studies where surveying was the subordinate method (e.g., an experimental study that uses a small follow-up survey) or where data was archival. This process resulted in a final set of 636 articles. Some articles reported multiple studies; thus, our sample for analysis totaled 679 studies (see Table 1).

Using our final sample, we examined each paper's method section (or its equivalent) and any relevant appendices to evaluate data quality procedures. If the authors referred the reader to an online-only appendix (e.g., "Further information on our handling of missing data can be found in Online Supplement C1."), we examined it to look for the communication of data quality procedures. By thoroughly

examining recent literature (described in Section 3), we identified six recommended best practices common to survey studies (see Table 2). While many more procedures could (and arguably should) be communicated, we sought to uncover the frequency of those whose absence would most clearly hinder statistical conclusion validity in most studies.

Year		Journal	
2008	41	EJIS	122
2009	39	ISJ	74
2010	47	ISR	78
2011	56	JAIS	98
2012	52	JIT	29
2013	47	JMIS	129
2014	40	JSIS	57
2015	65	MISQ	92
2016	31		
2017	43		
2018	46		
2019	57		
2020	70		
2021	45		

Table 1. Studies by Year and Journal

Procedure	Necessity
Inattention	Failure to remove inattentive respondents can inflate correlations between constructs (Huang et al., 2015).
Missing responses	Mishandling of missing data can lead to biased results or an unnecessary reduction in statistical power (Newman, 2014).
Outliers	"[T]he decisions that researchers make about how to define, identify, and handle outliers...change substantive conclusions including the presence or absence, direction, and size of an effect or relationship" (Aguinis et al., 2013, p. 272).
Normality	High levels of skewness can decrease statistical power in SEM analysis (Goodhue et al., 2012).
Common method bias	Common method bias can influence both within-construct and between-construct results (Schwarz et al., 2017)
Non-response bias	If non-respondents differ from respondents in a meaningful manner, results can be biased (Schneider et al., 2012).

Table 2. Data Quality Procedures Coded

We coded for any communication regarding the procedure for the six data quality procedures. For example, even if a paper mentioned that no missing data was found (and no procedure was required), we coded that procedure as being addressed. If a procedure was performed, it was documented along with the criteria used to gauge the procedure. Coding was executed in three passes using three different coders. Two coders independently assessed all 636 papers, coding for the data quality procedures outlined in Table 2. A third coder evaluated the papers that contained coding discrepancies and made final rulings.

2.2 Results

After coding the data, we conducted a series of analyses on data quality procedure communication in IS journal articles. This section presents our findings and discusses where problems exist and why they may occur.

2.2.1 Data Quality Procedure Communication. Our analysis revealed significant discrepancies in communication across different data quality procedures (see Table 3). Common method bias was the only procedure mentioned in more than half of the studies, with mentions of non-response bias approaching 50%. Missing data and normality were mentioned in around a third of the studies. Each of the other procedures was discussed in less than 15% of cases.

Note that this analysis only pertained to the mention of the procedures, not whether a problem was found. This makes the disparity more pronounced. While over 70% of studies discussed common method bias (with many noting no such bias present), under 10% of studies had a similar discussion of outliers. Although authors may have performed outlier detection methods, results from those methods were not communicated.

Procedure	Mentioned	Not Mentioned	Pct.
Inattention	101	578	14.87%
Missing Data	259	420	38.14%
Outliers	64	615	9.43%
Normality	222	457	32.70%
Common Method Bias	491	188	72.31%
Non-Response Bias	308	371	45.36%

Table 3. Data Quality Procedure Mentions

2.2.2 Data Quality Trends. We next examined trends in data quality procedures over time to determine whether the communication issues are improving. As indicated in Figure 1, most of the procedures remained consistent year-to-year. Normality was mentioned in nearly 50% of the studies in 2010, dropping off in the years that followed, only to begin to recover more recently. Communication of common method bias tests showed steady growth before leveling off. Inattention was largely stagnant from 2008 to 2018 before significantly improving from 2019 to 2021. This could be due to a stronger emphasis on inattention in the literature (e.g., Huang et al., 2015) or a response to the increased use of online panel data such as Amazon's Mechanical Turk (Jia et al., 2017). The emphasis on common method bias and inattention in the literature provides hope that greater emphasis on the totality of data quality procedures could have a measurable effect on their communication in published studies.

2.2.3 Data Quality Procedures by Journal. Additionally, we examined whether data quality procedures are communicated more often in some journals than others. Figure 2 shows some low-level variations among the journals, but the general trends were similar.

2.2.4 Summary of Results. These results indicate potential areas of improvement regarding the under-communication and, possibly, under-performance of data quality procedures. This is evident and easy to diagnose due to the attention paid to some fundamental procedures needed in most survey analyses. For example, only 15% of studies in our sample mentioned

checking for inattention, despite its potential for introducing error into statistical analysis, calls for its inclusion (e.g., Podsakoff et al., 2012), and its increasing prevalence in online surveys (Jia et al., 2017). The increased communication of inattention in recent years (2019-2021) is encouraging, demonstrating the value of creating awareness of the importance of these procedures.

Even allowing for some variation due to the unique nature of individual studies (e.g., qualitative surveys cannot address normality, shorter surveys may not require an assessment of inattention), it is reasonable to expect a higher percentage of studies to mention each of the data quality procedures we have highlighted. One possible explanation for lower communication of data quality procedures is lack of space. Journals impose character or page limits on research submissions. However, this explanation seems insufficient as the necessary space is small, and many journals allow high page counts for online-only appendices.

In addition to indicating a concern for our field, the under-communication of data quality procedures makes it more difficult for doctoral students to know how to conduct and communicate their work. Lacking clear external guidance, doctoral students must be educated in their programs on best practices in conducting data quality procedures. In support of that aim, we provide a toolkit for instructors and students regarding current best practices in data quality procedures. First, we summarize best practices into a categorized framework. Then, guided by current research, we offer recommendations on handling data quality procedures for each category.

3. "5-C FRAMEWORK" OF DATA QUALITY PROCEDURES

Data quality procedures refer to actions taken before, during, and after data collection to maximize data validity for analysis. This section presents a framework that can be taught within doctoral curricula to ensure proper coverage of best practices. The five categories presented (see Table 4) aim to provide order for a literature stream and a set of methodological processes often discussed independently. In our experience, while many of these procedures are mentioned across different courses in doctoral curricula, no focused effort provides comprehensive guidance that students can use when learning to design and conduct their own research.

Category	Definition
Correspondence	the degree to which all data in a data set fall within the intended sample frame of the study
Completeness	the degree to which all respondents fully answer all survey questions
Carefulness	the degree to which all respondents were attentive and engaged while taking the survey
Composition	the dispersion of the data after the survey is completed, specifically as relates to the normality of the data and the presence of any outliers
Credibility	the degree to which the results of a survey are free from any unnecessary methodological bias

Table 4. Categories of Data Quality Procedures

The procedures selected for a given study are subject to the demands of its methodology. Still, we can generalize our discussion by highlighting the most common procedures and how they relate to the broader objective of ensuring confidence in research findings. The naming convention used is a simplistic mnemonic device. The framework outlines core aspects of data quality that doctoral students can remember and follow when conducting their survey research.
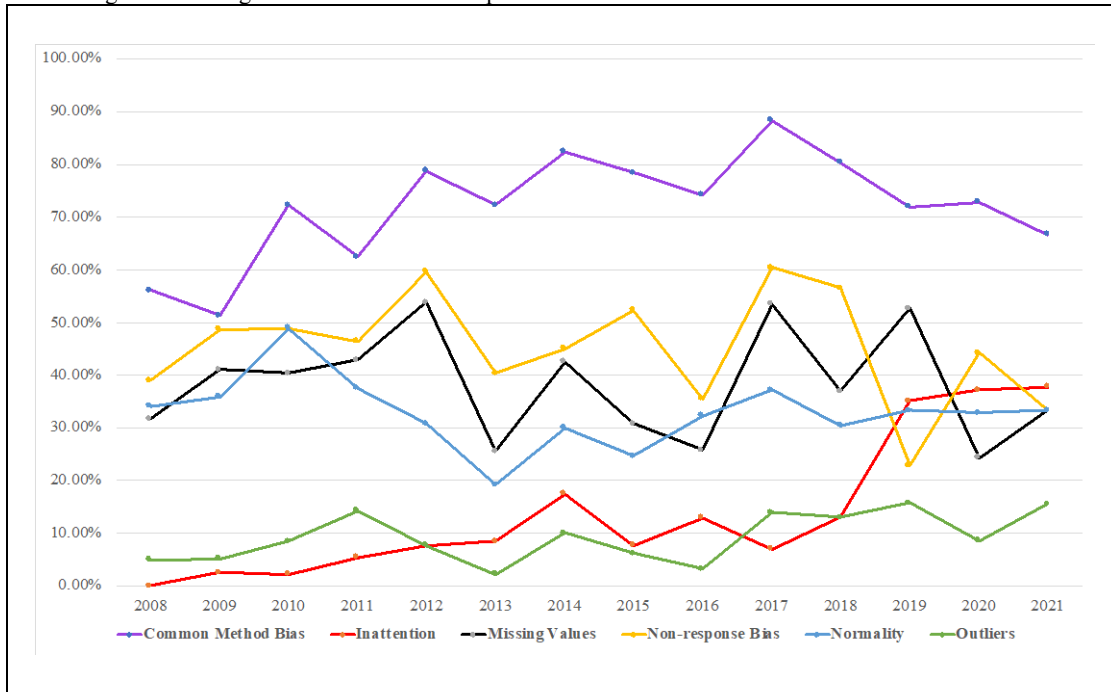

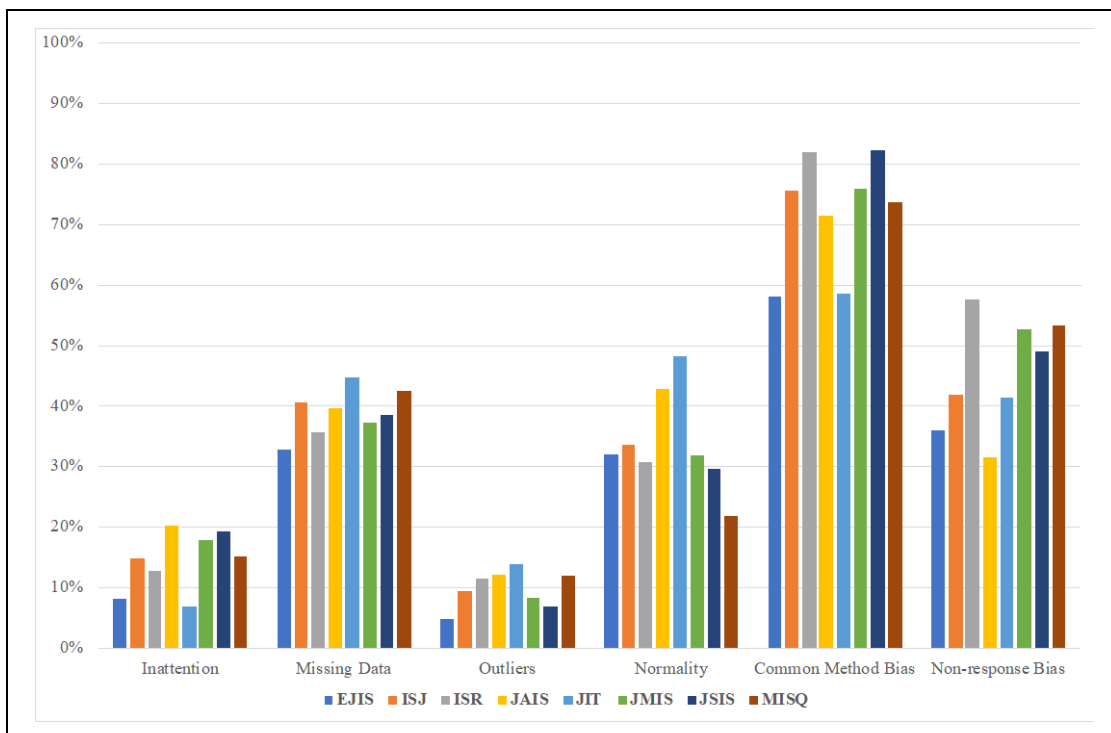**Figure 1. Mentions of Data Quality Procedures Over Time**

Figure 2. Data Quality Procedures by Journal

3.1 Correspondence

A study's conclusions are only valid if the data on which they are based are also valid. For example, a meteorologist would not report the temperature in Boston using a thermometer located in San Francisco. Thus, ensuring that data used in a study correctly corresponds to the intended target is essential for data quality. To that end, the correspondence of a data set pertains to the degree to which all the data it contains falls within the study's intended sample frame. Correspondence procedures include properly defining the intended sample frame, taking steps to prevent respondents outside the sample frame from taking the survey, and removing responses that do not adhere to the sample frame during analysis. When a study's sample frame does not match the population of interest, the study is prone to *coverage error* (Couper, 2000).

3.2 Completeness

The completeness of a data set pertains to the degree to which all respondents fully answer all necessary survey questions. Completeness procedures include steps taken to prevent respondents from actively skipping or accidentally overlooking any questions on a survey. They also involve steps taken after a survey is deployed to account for any missing data, including removal of responses or recalculation of missing responses.

Missing data have theoretical, practical, and statistical implications for knowledge generation (Schafer & Graham, 2002; Tsikriktsis, 2005). Theoretically, missing data could reveal an underlying bias in the sample if individuals with specific characteristics or preferences uniquely failed to complete all or part of the survey (Roth, 1994). Practically, missing data could indicate issues related to the reliability of the survey instrument if missing data can be traced to unnecessary difficulty in taking the survey or a faulty line of questioning that rendered the meaning of some or all of the questions unclear. Statistically, missing data alters how a data set is analyzed (Schafer & Graham, 2002). Thus, it is vital to safeguard against missing data where possible and communicate actions taken to remedy problems with missing data.

3.3 Carefulness

Carefulness pertains to the degree to which respondents were (in)attentive and (dis)engaged while taking the survey. Data gathered from inattentive respondents is unlikely to accurately represent their true values (Maniaci & Rogge, 2014). It is vital in survey analysis that data collected from respondents are authentic. Otherwise, any conclusions drawn from those responses are subject to skepticism.

Many surveys, especially those delivered remotely through an online medium (Huang et al., 2015) or through an online panel (Goodman et al., 2013), are prone to higher levels of inattention. In these cases, respondents either do not sufficiently read questions or provide adequate care in their responses, leading to overly (often impossibly) fast response times, straight-lining, patterned responses, etc. (Revilla, 2016). This category includes steps that can be taken to increase respondents' attention, verify that proper attention was paid during survey taking, and remove responses that indicate a lack of attention.

3.4 Composition

Composition pertains to the dispersion of the data after the survey is completed, as it relates to the normality of distribution and the presence of outliers. Composition procedures are almost entirely statistical, as little can be done during survey creation or administration to prevent skewed results or extreme responses. Nonetheless, examining data during data analysis is important to determine if actions must be taken to remedy any unnecessary influences on survey results.

Since many statistical analysis techniques are affected by composition, researchers should consider the dispersion of the data and the positioning of individual responses. Regarding the former, Goodhue et al. (2012) found that highly skewed and kurtotic data reduce power and can influence the results of smaller sample sizes in structural equation modeling (CB-SEM and PLS-SEM) and regression. With respect to individual responses, data should be examined for univariate and multivariate outliers (Osborne & Overbay, 2004).

3.5 Credibility

The credibility of a data set pertains to the degree to which the survey results are free from methodological bias due to the survey instrument. Biased data leads to biased results. One of the most common instrument biases encountered is common method bias (in which respondents' answers are influenced by the method selected) (MacKenzie & Podsakoff, 2012). When present, the conclusions drawn from the analysis are flawed, as the responses were unduly influenced by the method selected for the study. The goals of survey research must include extracting the purest information from the respondents without any unaccounted-for influences in the investigation. Thus, credibility procedures include the actions taken before and during survey administration to eliminate the threat of biases and the actions taken during data analysis to dispel any concerns that biases may have been present.

With the framework defined, we now discuss guidelines regarding enacting and communicating data quality procedures within each category. In the next section, we present guidance that can be used to educate doctoral students on current procedures.

4. GUIDELINES FOR DATA QUALITY PROCEDURES

While a review of all research concerning data quality procedures would be beyond the scope of a single journal article, this section draws on current thinking to summarize the most pertinent best practices for each category. In doing so, we offer guidelines that doctoral students can draw on for conducting, communicating, and evaluating survey research. The next section discusses how these guidelines can be incorporated into new or existing doctoral curricula.

We offer guidelines according to their temporal ordering when conducting survey research. Actions that are generally taken before and during data collection are termed *Procedural*. Actions taken after data collection, prior to conducting full data analysis, are termed *Statistical*.

It is important to note that every study has unique considerations regarding how best to ensure that the data gathered are of the highest quality possible. Thus, while the following guidelines offer a set of normative principles, we recognize that not every recommendation applies to every study. The responsibility for properly handling data quality concerns rests with researchers, and the appropriate actions will depend on the research context.

4.1 Correspondence

The goal of the correspondence category is to avoid coverage error (Groves, 1987), where the sample does not reflect the population of interest. Coverage error manifests when respondents who should be excluded are included or when respondents who should be included are excluded. In both cases, remedies can be employed to ensure proper correspondence.

4.1.1 Procedural. The first and somewhat obvious step in ensuring proper correspondence is to define the sample frame of the study clearly. Researchers should consider any unique characteristics of respondents that should either be included or excluded from the sample. For example, it is common to draw from student samples (Steelman et al., 2014), yet student samples are often not representative of the general populace in terms of age.

Procedurally, once the sample frame has been properly identified, the goal is to ensure that alignment between the sample and population is maintained during data collection. Numerous techniques have been offered for this purpose. One technique is to include qualification tests and additional questions in the survey that assess whether each respondent meets the sample frame requirements (Cheung et al., 2017). These additional questions could be explicit (e.g., demographic questions) or more subtle, with questions only answerable by those within the sample frame (Cheung et al., 2017). For example, a survey seeking software product users could ask how long they have used the software, eliminating responses from those who lack experience.

For proper inclusion, one common technique is the use of incentives, where a reward is offered for the completion of the survey (Parsons & Manierre, 2014). Incentives encourage participation to ensure that adequate responses are received to cover the sample frame. Qualification questions, as discussed above, can also be used to ensure proper inclusion, as they allow for later assessment of sample frame coverage.

4.1.2 Statistical. Most of the work to ensure correspondence is procedural but confirmation can be achieved statistically by examining demographic characteristics. For example, if the sample frame calls for working professionals, that characteristic could be inspected. If any qualification tests were included in the survey, these will be examined here.

Beyond examining demographic characteristics, other actions can be taken to improve the correspondence of the data. Non-response error is a common threat to sample research. This error occurs if respondents are meaningfully different from those who do not respond. One common technique for evaluating non-response error is to conduct a wave analysis (Armstrong & Overton, 1977), where the characteristics of early and late respondents are compared to see if there is a difference in later respondents. Later respondents are presumed to be more like non-respondents than early respondents, thus allowing for comparison. In addition, researchers should check their data set for duplicate entries (same responses) or duplicate respondents (same person, different responses) (Woo et al., 2015). Many surveying programs capture the IP address of respondents, which allows for the identification of duplicates in some cases (Aust et al., 2013).

4.2 Completeness

The completeness category aims to minimize the presence and impact of missing data, i.e., data missing within responses—called *item non-response* (Fichman & Cummings, 2003)—rather than data missing across an entire response where the resolution is clear. It is common for researchers to minimize the importance of examining missing data, with many neglecting to discuss the problem. Roth (1994) found that well over 50% of articles in two prominent organizational behavior journals failed to mention missing data in their text. Our analysis uncovered a similar problem in IS journals. This section highlights what students should be taught about mitigating missing data problems and how to communicate the actions taken.

4.2.1 Procedural. Procedurally, the goal is to minimize missing data as much as possible. This aim has limitations, as ethical guidelines often mandate the voluntariness of data collection (Newman, 2014). Consequently, while the most obvious action is to require respondents to answer all survey questions, this should be implemented with care, as privacy concerns and data accuracy may override benefits. If missing data are expected, then the focus shifts to minimizing the impact of missing data on subsequent analyses. Because removing missing data can dramatically impact statistical power, it is often necessary to collect more responses than required.

4.2.2 Statistical. The statistical component of completeness procedures aims to identify and correct any problems associated with missing data after data collection. Inaction toward missing data is impossible, as statistical software programs will take action even if no decision is made (Fichman & Cummings, 2003). Therefore, selecting the most appropriate statistical remedy is important.

The first step in statistically handling missing data is to determine if there is a pattern or cause behind the missing data. There are three primary designations to missing data: missing at random (MAR), due to values on a different variable (e.g., all males neglected to answer a certain survey question); missing not at random (MNAR), due to values on the same variable (e.g., individuals who smoke fail to answer 'yes' to a question about smoking); and missing completely at random (MCAR), due to no identifiable reason (Little & Rubin, 1989). Both MAR and MNAR data may be biased; thus, the solution may be unique to the situation. MCAR data, however, can be resolved in several ways.

When data are MCAR, options for dealing with missing data fall into two main categories: deletion and replacement. Deletion techniques remove responses from subsequent analyses, while replacement techniques seek to fill in missing data with likely values. For a straightforward decision tree regarding missing data techniques, see Newman (2014).

Listwise deletion and pairwise deletion are two commonly used deletion techniques. Listwise deletion removes all values from a respondent with any missing data, whereas pairwise deletion removes values only for analyses that involve the missing data. While listwise deletion is the most used technique for handling missing data, it is also the most often criticized due to its removal of viable data (Newman, 2014). In our sample, most of the 259 studies that discussed missing data utilized listwise deletion, thereby removing all cases with incomplete data. Pairwise deletion is also problematic since it creates

unequal sample sizes for different analyses (Fichman & Cummings, 2003). Thus, while some recommend pairwise deletion (e.g., Roth, 1994), other more robust techniques are available and are strongly recommended.

Replacement techniques are more complex than deletion techniques but can provide greater value in statistical analysis. These techniques can be subdivided into single imputation and multiple imputation techniques. With a single imputation, the mean value across a variable (mean substitution) or a predicted value based on other related values (maximum likelihood) replaces missing data. In multiple imputation, multiple values are estimated from the distribution of the observed data and used to replace missing data. Both techniques have drawbacks but are often preferred to deletion. Multiple imputation is valuable in inferential analysis and is recommended by many (e.g., Fichman & Cummings, 2003).

4.3 Carefulness

The carefulness category aims to minimize the impact of careless responses in surveys. Careless responses are those that deviate from a respondent's true value, thus introducing additional errors in subsequent data analyses (Meade & Craig, 2011). Common types of carelessness in surveys include straight-lining, where respondents provide the same response to an improbable number of consecutive questions; patterned responses, where respondents use a zig-zag or other recognizable pattern; and speeding, where respondents complete the survey in an improbably short amount of time. The presence and impact of careless responses can be minimized through procedural and statistical techniques.

4.3.1 Procedural. Procedurally, the amount of carelessness can be reduced by increasing respondents' attention. The impact of carelessness can be reduced by identifying careless responses in statistical analysis. There are several ways to increase respondents' attention. For example, attention can be increased by reducing the difficulty or length of surveys, using respondents with greater ability to complete the survey task, or motivating respondents (Krosnick et al., 1996). Incentives can also entice respondents to provide quality responses (Cole et al., 2015). Direct intervention provides feedback when careless responses begin to occur (Zhang & Conrad, 2018).

Procedurally, covert or overt attention check questions make it possible to identify careless respondents. Covert attention checks seek to identify careless respondents without their knowledge by asking questions that only highly attentive respondents could answer correctly. One form of covert attention check is the Instructional Manipulation Check (IMC) (Oppenheimer et al., 2009). IMCs include a question(s) that has similar instructions to other questions in the survey, then subtly asks the respondents to ignore the instructions and provide a unique response. While the IMC technique is somewhat complex, simpler forms of covert attention checks can also be used, such as including bogus items (Meade & Craig, 2011) or screeners (Berinsky et al., 2014). These are questions, such as "Are you at least three years old?" or (on a Likert scale), "The Sun is very cold" that attentive respondents could answer easily.

Overt attention checks explicitly ask respondents about the degree to which they paid attention while answering the survey questions. These include participant engagement items (Meade & Craig, 2011) or seriousness checks (Aust et al., 2013). In both cases, respondents are asked (usually at the end of a survey) how much attention they gave to answering survey questions. Respondents who indicate a lack of attention can be identified as careless respondents.

Despite their stated benefits, attention check questions, if mishandled, can do more harm than good. Vannette (2017) notes that attention check questions may induce bad behavior when respondents are made aware they are being watched. Additionally, the immediate removal of respondents who fail attention check questions may bias the results, as the subset of seemingly inattentive respondents may not be proportionally distributed within the sample frame. Consequently, covert attention checks may be best, as they are less likely to induce bad behavior. Alternatively, attention checks can be placed at the end of a survey when all other survey questions have been answered.

4.3.2 Statistical

Once survey data have been received, the aim is to identify and account for any carelessness that may have occurred during data collection. Responses that can reasonably be determined to be different from the respondent's actual values due to inattention should be eliminated. Aust et al. (2013) wisely recommend that researchers decide their inclusion/exclusion criteria for identifying inattention before examining the data to avoid the temptation to remove cases based on criteria that might improve results.

Our literature review found no ideal set of criteria for identifying careless responses. Certainly, using procedural methods to draw out inattention will mitigate potential problems. Beyond these, numerous statistical remedies have been identified in the literature. We echo Curran's (2016) recommendation that using multiple criteria may be best, as most have benefits and drawbacks to consider. The following is a list of commonly recommended criteria:

- Within-person correlation (Meade & Craig, 2011) – inattention identified through improbably high correlation among disparate survey questions.
- Long string (Meade & Craig, 2011) – inattention identified through an exceedingly high number of consecutive questions with the same response.
- Speedy response (Aust et al., 2013; Meade & Craig, 2011; Zhang & Conrad, 2018) – inattention identified through overly fast response across the entire survey. While it is difficult to determine a proper threshold for what can be considered *overly fast* (Aust et al., 2013), one conservative recommendation is 300 milliseconds per word in the question (Zhang & Conrad, 2018).
- Mahalanobis Distance (Meade & Craig, 2011) – inattention identified by calculating the Mahalanobis Distance for all responses across the survey. While other criteria seek to identify overly similar responses, this criterion seeks to identify overly dissimilar responses.
- Impossible responses – inattention identified through the recognition that one or more responses are not possible. For example, percentages listed above 100 or 'yes' and 'no' answers to congruent questions (Schmitt & Stuits, 1985) may be flagged.

Other considerations are important when accounting for carelessness. For example, it is important to avoid impacting

the sample frame when removing responses (Berinsky et al., 2014). Bias can be inadvertently introduced if an unrepresentative portion of the sample frame is removed before analysis (Anduiza & Galais, 2016). Still, when carelessness is suitably managed, researchers can have more confidence in the validity of their data set.

4.4 Composition

The composition category aims to minimize the impact of outliers and non-normal data on statistical analyses. Outliers, by definition, exert a disproportionate impact compared to other values (Aguinis et al., 2013). As such, they must be handled properly to ensure that subsequent analyses can be completed. In many statistical analyses—for example, covariance-based structural equation modeling (CB-SEM)–the assumption of a normally distributed data set is required to analyze the data (Hair et al., 2011). Even partial least squares (PLS) path modeling, often presented as a technique resistant to such issues, can be influenced by extreme non-normality, inflating standard errors (Hair et al., 2016). Skewed data can reduce statistical power in regression, CB-SEM, and PLS (Goodhue et al., 2012). Thus, it is imperative to assess the distribution of data before conducting statistical analyses.

4.4.1 Procedural. Procedurally, not much can be done to prevent honest outliers or skewed data during data collection. One recommendation would be to consider what Aguinis et al. (2013) term *interesting outliers* or outliers due to an unforeseen cause. For example, perhaps a respondent provides an extremely high value for a question because they speak a second language. In this case, the outlier could be prevented by considering the possible implications of multilingualism beforehand. In most cases, most of the work on composition will be performed after data are collected.

4.4.2 Statistical. In this section, we divide our discussion of best practices into recommendations for the two aspects of data composition: outliers and normality. We draw attention to Aguinis et al. (2013) for a complete treatise on outliers. Outlier handling pertains to two primary activities: outlier detection and outlier response. While detecting outliers can be difficult, one recommendation is to use visual and statistical means to find cases far outside the norm (Aguinis et al., 2013). Mahalanobis' distance is a form of multivariate outlier detection, looking for cases that deviate from others across multiple variables (Aguinis et al., 2013). Researchers could use not only the calculated Mahalanobis' distance (statistical), but also a graphical representation of all such values (visual) to find outliers. Similarly, a boxplot (Hair et al., 2016) provides a visual representation that might make detection easier. Once outliers are detected, a proper response is required. Aguinis et al. (2013) identified twenty recommended methods for handling outliers. Whatever method is used to account for outliers, be it removal or respecification, researchers should check if removing outliers influences results (Aguinis et al., 2013). If it does, the results before and after removal should be reported.

Normality is easier to assess than outlier identification. Skewness and kurtosis are two common statistics used to determine normality (Hair et al., 2016). Skewness measures the relation of the mean to the median, detecting if an equal number of cases are above and below the mean, while kurtosis measures

the horizontal distribution of the cases, detecting if an abnormal number of cases are bunched close to the mean or to the extremes. If data are too skewed or too kurtotic, the entire data set (or individual variables) can be transformed to return to a more normal distribution (Gao et al., 2008; Tabachnick & Fidell, 2007). In more extreme cases of non-normality, a two-step transformation has proven effective (Templeton et al., 2021). However, transformations should only be carried out when necessary and should align with the selected analysis technique (Rönkkö et al., 2021).

4.5 Credibility

The credibility category aims to evaluate and eliminate any aspects of the survey instrument that may bias results. While the other categories primarily focus on issues surrounding survey responses, this category evaluates the instrument used to elicit those responses and asks whether any inherent bias may be present. When the instrument is the source of biased results, we refer to it as *method bias* (Podsakoff et al., 2012). Arguably, the most widely known instance of method bias is common method bias, whereby respondents answer questions with a common method similarly, regardless of the question being asked (Podsakoff et al., 2003). As common method bias has been extensively covered in IS literature (e.g., Aguirre-Urreta & Hu, 2019; Chin et al., 2012; Schwarz et al., 2017; Sharma et al., 2009), we will focus on other sources of method bias in survey research.

4.5.1 Procedural. For an excellent, detailed accounting of procedures for reducing method bias, see Podsakoff et al. (2012). The authors describe the importance of including variation in survey item wording and placement among their many recommendations. A preceding survey question can often influence the following question (Krosnick et al., 1996). Therefore, researchers are recommended to separate constructs hypothesized to be related (Podsakoff et al., 2012) or intermix items from different constructs (Wilson et al., 2017).

Another chief concern for survey credibility is social desirability bias, or the tendency among respondents to answer survey questions in such a manner as to present themselves favorably (Fisher, 1993). Thus, an important aspect of survey design is considering whether any questions evoke a socially desirable response (Berinsky et al., 2014). As a remedy, researchers can ask indirect questions that invite respondents to consider the question from another's point of view (Fisher, 1993). Doing so may allow researchers to capture respondents' actual attitudes, since responses to hypotheticals often indicate true personal values (Simon & Simon, 1974).

4.5.2 Statistical. Beyond assessing common method bias, most of the work performed to ensure proper credibility occurs before data are collected. After data collection, it is challenging to ensure other biases are present if procedural remedies are not implemented. For example, post hoc assessments of social desirability bias are unlikely to be beneficial, as researchers rarely know the true values of survey respondents. Podsakoff et al. (2012) recommend directly measuring and assessing any known sources of method bias in a survey. Careful consideration before the survey is released is necessary to avoid issues with credibility during statistical evaluation.

5. DISCUSSION

To effectively educate our doctoral students on data quality procedures, we must prioritize the topic in our curricula and utilize a common framework. In this paper, we presented a framework and set of guidelines aiming to frame discussions on best practices. As noted earlier, each study has unique considerations for ensuring the quality of data collected, and researchers bear the responsibility of deciding how best to handle data quality concerns based on their specific circumstances. Nonetheless, the 5-C framework, summarized in Table 5, offers a common approach to communicating data quality procedures in IS survey research.

5.1 Pedagogical Recommendations
Whereas no standard curriculum for doctoral programs exists, we can outline our curricular recommendations by understanding the four facets of doctoral education – Learn, Practice, Evaluate, and Demonstrate.

Regarding learning, the most straightforward way to utilize this framework is to integrate it into doctoral courses or seminars. Depending on the curriculum in place, it may need to be taught in multiple courses. For example, a statistics course could focus on the Composition category, while a more traditional methods course could focus on the other four. Another approach could be to separate the procedural and statistical guidelines, teaching them in separate courses. If taught in a seminar format, exemplar papers could illustrate not only how to conduct the procedures but how to report them in published research.

Regarding practice, data quality procedures must be performed to be learned well. We recommend that students be exposed to actual (or more realistic) data sets, not those that have already been cleaned and prepared. Students should get this practice both in coursework and through involvement in research projects, preferably alongside those more senior in the field.

Regarding evaluation, we recommend that data quality procedures be incorporated into student comprehensive examinations. This could take on a variety of forms. In a timed exam, students could be asked to spell out the procedures that should be enacted for a given study. In a practical exam, students could be asked to prepare a data set for statistical analysis, conducting data quality procedures as necessary.

Regarding demonstration, we recommend that dissertation committees include data quality procedures to evaluate student dissertations using survey methodologies. The pertinent questions outlined in Table 5 should be applied as part of this evaluation. Not only will this aid in ensuring more students are prepared for conducting future survey research, but it will also provide our field with clear illustrations of proper data handling.

5-C Category	Pertinent Questions	Editorial Recommendations
Correspondence	Are all respondents within the sample frame? Is the entire sample frame covered by the respondents?	1. Initial and final sample sizes 2. Sample frame characteristics 3. Procedure(s) used to ensure correspondence 4. Response rate 5. Test for non-response error 6. Statistical evidence of sample frame coverage
Completeness	Did all respondents provide complete responses? If not, what actions were taken to ensure that missing data did not bias the results?	1. Procedure(s) used to reduce missing data 2. Amount/categories of missing data (even if none) 3. Procedure(s) used to account for any missing data
Carefulness	Were all respondents attentive when providing their responses? If not, what actions were taken to ensure that the careless responses did not influence the results?	1. Procedure(s) used to detect carelessness 2. Inclusion/exclusion criteria 3. Number of cases that indicated carelessness (even if none) 4. Action(s) taken to account for careless responses
Composition	Does the data contain any outliers which may influence the results? Does the composition of the data violate any statistical assumptions pertaining to normality?	1. Procedure(s) used to detect outliers 2. Number of univariate/multivariate outliers (even if none) 3. Action(s) taken to account for outliers 1. Procedure(s) used to detect issues with normality 2. Normality of data set 3. Action(s) taken to account for issues with normality
Credibility	Does any aspect of the survey instrument potentially bias the results? If so, what actions were taken to eliminate the influence of such bias(es)?	1. Potential sources of method bias 2. Determination as to whether bias(es) are present 3. Procedure(s) used to account for any known bias(es)

Table 5. Data Quality Recommendation

6. LIMITATIONS

While our analysis of IS survey research aimed to be as comprehensive as possible, we cannot guarantee that we identified every survey paper in the fourteen-year period. Some studies were borderline for inclusion in our analysis, such as those that utilized a brief sample, used samples as part of larger data collections, or used samples to develop new measures. We took a conservative approach in our selection, including only those that we were most certain matched our criteria. Despite the inherent challenge, we have reason to be confident that we sampled most survey studies within our time period.

Similarly, due to the lack of established norms regarding data quality procedure communication, we cannot guarantee that we identified every procedure in every study under consideration. Authors use different wording schemes to describe similar procedures and communicate data quality procedures in various places within a manuscript (e.g., main body, footnotes, endnotes, and appendices). We utilized multiple coders to increase our coding accuracy to the extent possible.

The complexity of survey studies means that not every study will require the same data quality procedures. For example, a survey with Likert scale questions will have different data from a survey with ranked-choice questions. Therefore, we aimed to avoid the insinuation that all six of the data quality procedures in our data analysis were mandatory for every study. Rather, we expect a high percentage for each. Future researchers can extend our findings by analyzing the appropriateness of the data quality procedures in each article. Doing so would provide an even stronger assessment of whether the appropriate procedures are followed.

Finally, we note that our investigation and discussion centered on data quality procedures in survey studies. Doctoral students should be knowledgeable about numerous methodologies. Therefore, we encourage scholars to develop similar curricular frameworks for other forms of scientific study.

7. CONCLUSION

Transparency in data quality procedure communication is of vital importance in survey research. Knowing which procedures to enact and how to communicate those procedures can be difficult. We hope the framework and best practices discussed here can help prepare doctoral students to effectively enact and communicate data quality procedures.

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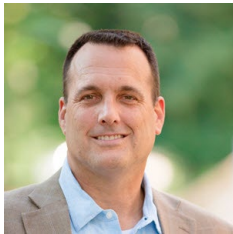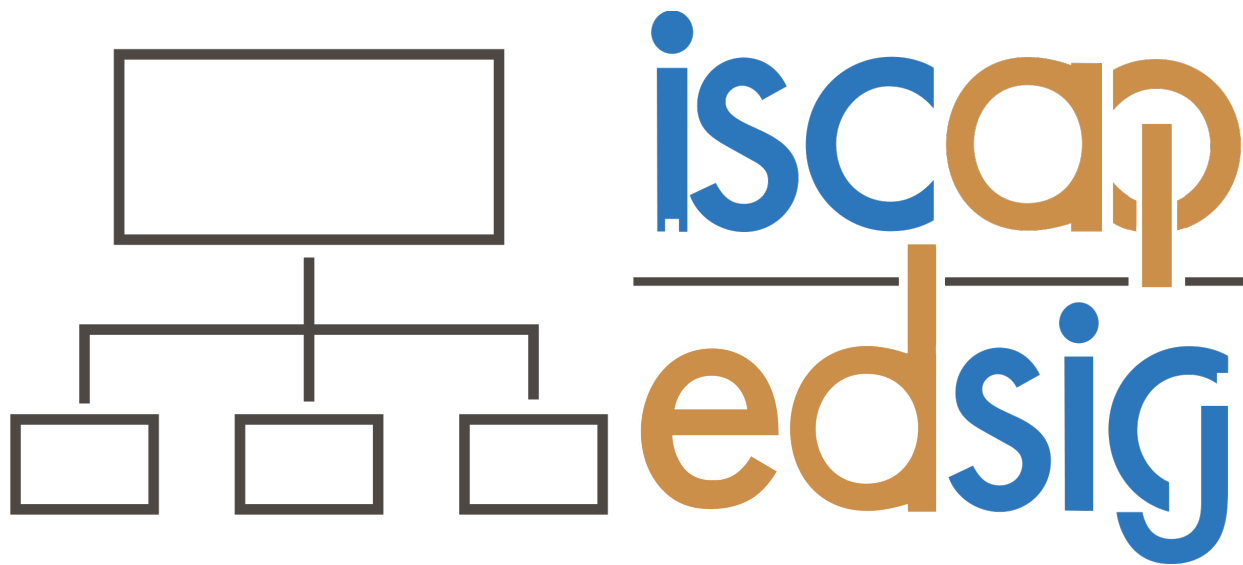
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