



Preventing human error: The impact of data entry methods on data accuracy and statistical results

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ABSTRACT

Human data entry can result in errors that ruin statistical results and conclusions. A single data entry error can make a moderate correlation turn to zero and a significant *t*-test non-significant. Therefore, researchers should design and use human computer interactions that minimize data entry errors. In this paper, 195 undergraduates were randomly assigned to three data entry methods: double entry, visual checking, and single entry. After training in their assigned method, participants entered 30 data sheets, each containing six types of data. Visual checking resulted in 2958% more errors than double entry, and was not significantly better than single entry. These data entry errors sometimes had terrible effects on coefficient alphas, correlations, and *t*-tests. For example, 66% of the visual checking participants produced incorrect values for coefficient alpha, which was sometimes wrong by more than .40. Moreover, these data entry errors would be hard to detect: Only 0.06% of the errors were blank or outside of the allowable range for the variables. Thus, researchers cannot rely upon histograms and frequency tables to detect data entry errors. Single entry and visual checking should be replaced with more effective data entry methods, such as double entry.

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1. Introduction

To err is human. When humans do data entry, errors are therefore expected. Unfortunately, data entry errors can have devastating effects on research results. Simple data entry errors – such as typing an incorrect number, typing a number twice, or skipping a line – can ruin the results of a statistical analysis. As we will demonstrate, a single data entry error can make a moderate correlation turn to zero or make a significant *t*-test non-significant. Just one or two serious data entry errors can completely alter (and invalidate) a statistical analysis (Kruskal, 1960; Velleman & Hoaglin, 1995; Wilcox, 1998). Because data entry errors can be so devastating, researchers sometimes spend considerable effort to identify and correct the most severe errors. Researchers use preventative efforts such as doing all data entry themselves, entering data twice, and checking entries visually (Beaty, 1999; Cummings & Masten,

1994; Winkler, 2004). Researchers also use corrective efforts such as using graphs and diagnostic statistics to identify outliers (Mavridis & Moustaki, 2008; Tukey, 1977) and using advanced statistical techniques that may be less sensitive to outliers (e.g., Howard, 1976; Kulinskaya & Staudte, 2006; Ye-Mao, Xin-Yuan & Sik-Yum, 2009; Wilcox, 2008; Yuan & Zhong, 2008). None of these techniques is likely to be as effective as preventing the data entry errors in the first place. The purpose of this paper is to compare three data entry systems: two systems that are intended to eliminate human data entry errors at their source, and a control condition where data were entered once and were not checked.

1.1. The effect of data entry errors

Data entry errors can have serious effects on the results of a statistical analysis. We will consider two examples of this. Both examples use the first 50 males and first 50 females from a larger data set. These participants completed two items that measure aspects of neuroticism ("I get stressed out easily" and "I worry about things"). Each item was measured using a 5-point scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

For the first example, we examined the effects of a single data entry error on a correlation. In the original data, the correlation between the two items, as expected, was moderate, positive, and

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statistically significant ($r(98) = .56, p < .001$). This indicates that both items measure the same general construct. We introduced one data entry error on one variable for one participant (we changed a value of "5" to "55"), and this made the correlation near zero and non-significant ($r(98) = .02, p = .833$). This single data entry error suggests that worry and stress are unrelated, or that one of these items is an invalid measure of the construct we were trying to assess. These results demonstrate the well-known effect of outliers on correlations. Such outliers will also affect coefficient alpha (Lui, Wu, & Zumbo, 2010; Yan & Zumbo, 2007) and multivariate techniques that are based upon correlations (e.g., factor analysis, Bollen, 1987; and structural equation modeling, Ye-Mao et al., 2009). Data entry errors can easily introduce these types of outliers.

For the second example, we compared males and females on the item "I get stressed out easily." In the original data, the difference was statistically significant, with women obtaining higher average scores (men Mean = 2.60, women Mean = 3.42; $t(98) = 3.77, p < .001$). We introduced a single data entry error for one male participant (we changed one value from "2" to "22"), which made the difference no longer significant ($t(98) = .95, p = .347$). The original data indicated that women are more emotional than men, but this single data entry error suggests that there is no sex difference. These results demonstrate the effect of data entry errors on procedures that compare two means, and will generalize to procedures that compare several groups (e.g., ANOVA) and procedures that compare several groups on several variables (e.g., MANOVA; see Wilcox, 1998).

Most researchers realize that data entry errors can seriously affect the results of their statistical analyses and in extreme cases could reverse their substantive conclusions. Some researchers are so concerned about data entry errors that they avoid data entry altogether by using expensive optical scanning technologies or by having participants enter their own data during computer-administered studies. But for some types of participants (e.g., children) and research variables (e.g., field observations), and for researchers with limited money or technical skills, paper based measures – and human data entry – are still necessary. This paper will compare two methods of preventing and catching errors during the data entry process.

1.2. Methods of correcting data entry errors

There are two common methods of preventing and catching data entry errors: visual checking and double entry. In single entry with visual checking, the person enters the data once, often in a spreadsheet such as Excel or a statistical package such as SPSS. After entering the data, the same person visually compares the entries against the original paper measures. When discrepancies are found, the person corrects the errors. A variation of this approach is to have one person read the entries aloud while another person visually compares them to the original data sheet.

In double entry with checking for mismatches and out-of-range values, one person enters the data twice. The computer then compares these entries to identify mismatches. When mismatches are identified, the data entry person checks the original paper measure to determine the correct value. At the same time, the computer can check that all entries are within the allowable range. For example, on a 5-point agreement scale, all entries should be between 1 and 5. Out-of-range values can be highlighted, and the data entry person can then correct the errors. A variation of the double entry approach is to have two different people enter the data, which are then compared.

Some people (Burchinal & Neebe, 2006) and organizations (Cameron, Ewen, Ross-Degnan, Ball, & Laing, 2008) recommend double entry. However, empirical evidence is needed to determine

which data entry methods work the best. Two small-sample studies (Kawado et al., 2003; Reynolds-Haertle & McBride, 1992) have been conducted using paid medical professionals with extensive data entry experience, but there has been no research using the kinds of data and data entry personnel that we use in psychology. The current study used several different types of data that are commonly encountered in psychological research settings and used participants who are similar to the research assistants used in academic research. In addition, the current study examined the practical consequences of data entry errors. In research studies, the typical data entry error is small (typing a 4 instead of a 1). Are such data entry errors frequent enough or severe enough to influence published results and conclusions? The current study examined the effect of data entry methods not just on accuracy rates (as previous research has done), but also on statistical analyses that are done using the data that has been entered – coefficient alpha, correlations, and t -tests.

2. Materials and methods

2.1. Participants

A total of 195 undergraduate students (65 male, 130 female) participated in this study in return for course credit. Participants ranged in age from 18 to 44 years (Mean = 21, SD = 5). Of these, 163 (83.6%) reported that they were "Moderately comfortable" or "Very comfortable" with using computers, and only 10 students (5.1%) reported that they were "Moderately uncomfortable" or "Very uncomfortable." None of these students had done data entry before.

2.2. Procedures

Data were collected during 90-min one-on-one supervised sessions. Because the data entry was completed using Microsoft Excel, participants first watched a short video on how to use Excel. Next, the computer randomly assigned participants to one of the three data entry methods (using the random number generator at www.random.org), and showed participants a video on that data entry method. The first group was taught to enter the data twice and to locate and correct their errors using mismatch and out-of-range counters built into the Excel worksheet. See Fig. 1. The second group was taught to enter the data once and to check the data visually by comparing the typed entries with the original paper sheets. The third group was taught to enter the data once; they were told that accuracy was more important than speed, and to please be as accurate as they could.

After participants had received training in Excel and in their specific data entry method, they completed a practice session where they entered five data sheets. During this time, the study administrator provided participants with assistance and corrected any procedural errors they were making. Finally, participants completed the main data entry, which consisted of 30 data sheets.

Each data sheet contained six types of information: an ID number for the hypothetical participant (sequential numbers starting from 101), Sex (M F), and four 10-item measures. The four measures used three-point scales and five-point scales, with letters and numbers. See Appendix for a sample data sheet. To increase the difficulty of the data entry, participants were instructed to type only numbers. For example, participants typed 1 2 3 4 5 instead of SD D N A SA. In principle, it is bad practice to recode data while it is being entered. We included this type of data entry task because it may be common in research settings and because it will provide a stringent test of the effectiveness of the data entry methods. It may be that double entry or visual checking is suffi-

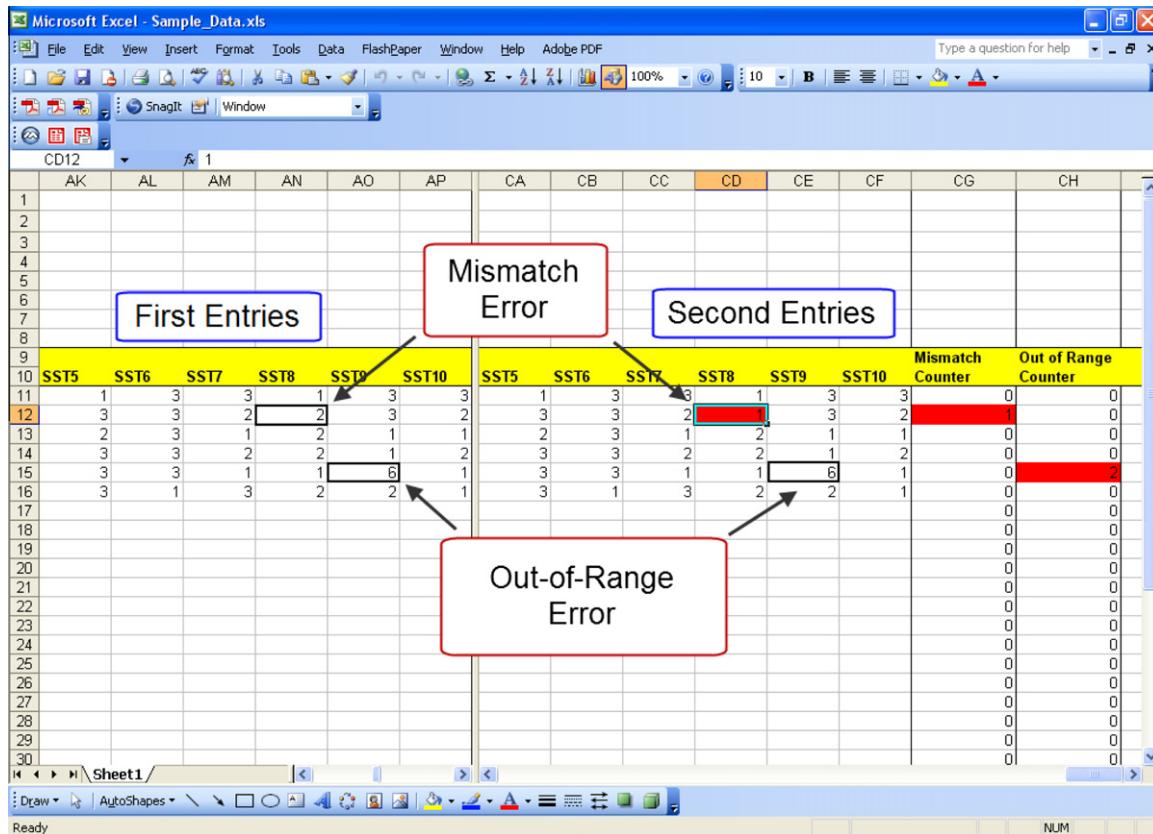


Fig. 1. Double entry screen layout.

cient to catch and remove the errors introduced by this more difficult task.

2.3. Data analysis

The 195 participants in our study are taking the role of research assistants, each of whom is entering the complete data set for an imaginary study with 30 participants. When our participants make data entry errors, this is mimicking a situation where a research assistant makes data entry errors and the published results are wrong. Accuracy was calculated as the percentage agreement between the responses entered by each participant and the correct responses. To examine the effect of data entry errors on research results, we calculated three statistics based upon the data that our participants entered: coefficient alpha, correlations, and independent sample *t*-tests.

2.4. Data screening

Data were screened carefully to ensure a fair comparison of the three data entry methods. In particular, data were removed for six participants who failed to enter data according to the instructions. First, participants sometimes entered the scales in the wrong order: They reversed the order of the second and third measures (Extraversion and School Experiences), resulting in extremely low accuracy scores, meaningless scale scores, and also some values that were out of range. Second, one participant entered incorrect ID numbers for most data sheets, resulting in extremely low accuracy scores. These catastrophic errors occurred for two of the single entry participants and four of the visual checking participants, but

none of the double entry participants (the differences in frequencies of catastrophic errors did not differ significantly by condition, Likelihood ratio (4) = 5.355, $p = .253$). These participants were eliminated from the remaining analyses.

3. Results

3.1. Time

Double entry took 33% longer than visual checking, which took 25% longer than single entry (49.73 min, 37.43 min, and 30.03 min, on average, respectively). These differences were statistically significant ($F(2, 164) = 55.54, p < .001$).

3.2. Accuracy

Double entry was more accurate than visual checking and single entry, but visual checking was no more accurate than single entry. See Table 1. Overall, 77.4% of the participants in the double entry condition had perfect accuracy, compared to 17.1% for visual checking and 5.5% for single entry ($\text{Chi-square}(2) = 83.80, p < .001$). Visual checking was slightly more accurate than single entry, but this difference did not reach statistical significance (Tukey's HSD $p = .843$). We conclude that visual checking is no more accurate than single entry. Therefore, we do not recommend that researchers use visual checking by a single person, given that it takes more time than single entry and has no apparent benefit.

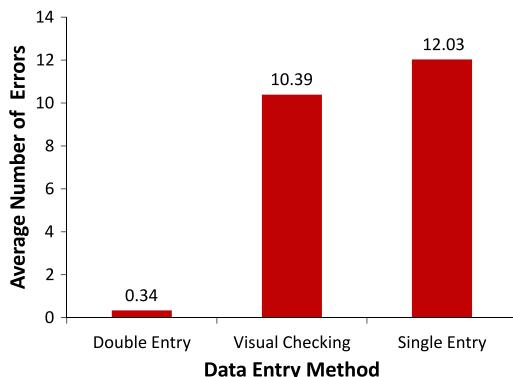
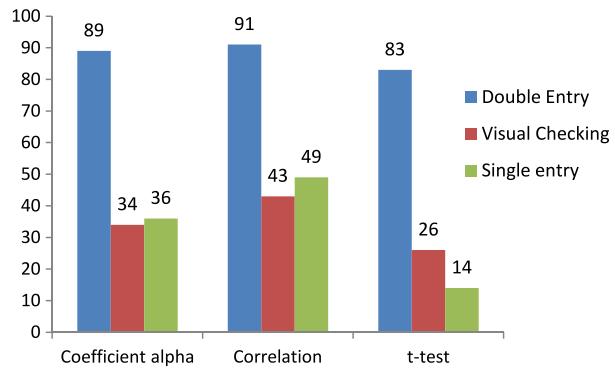
Although visual checking and single entry rarely resulted in perfect accuracy, all three data entry techniques had high average accuracy rates. This may give the impression that the differences

Table 1

Accuracy of the three data entry methods.

Data type	Data entry method						ANOVA	
	Double entry		Visual checking		Single entry			
	M	SD	M	SD	M	SD		
ID	1.0000	.0000	.9990	.0080	.9968	.0160	$F(2 192) = 1.53, p = .220$	
Sex	1.0000 ^a	.0000	.9924 ^b	.0190	.9949 ^{a,b}	.0155	$F(2 192) = 4.08, p = .018$	
FB 5 letters	.9996 ^a	.0011	.9884 ^b	.0192	.9847 ^b	.0276	$F(2 192) = 8.55, p = .000$	
Ex 5 numbers	1.0000 ^a	.0000	.9917 ^b	.0175	.9919 ^b	.0221	$F(2 192) = 4.48, p = .013$	
SE 3 letters	.9993 ^a	.0021	.9896 ^b	.0153	.9896 ^b	.0207	$F(2 192) = 7.46, p = .001$	
SST 3 numbers	.9999 ^a	.0005	.9965 ^{a,b}	.0091	.9946 ^b	.0143	$F(2 192) = 4.18, p = .017$	
Overall	.9997 ^a	.0006	.9918 ^b	.0129	.9905 ^b	.0191	$F(2 192) = 7.54, p = .001$	
Confidence Interval	[.9996, .9999]		[.9887, .9948]		[.9860, .9949]			

Note: FB = Family Background. Ex = Extraversion. SE = School Experiences. SST = Social Skills Test. Confidence Interval = 95% Confidence Interval for the mean. Within rows, means with different superscripted letters are significantly different at $p < .05$.

**Fig. 2.** Average number of errors.**Fig. 3.** Percentage of participants who obtained correct values for each statistic.

between the systems are statistically significant but not important: This is not the case. We calculated the average number of errors that participants made. Participants in the double entry condition made an average of 0.34 errors across the 1260 entries; participants in the visual checking condition made an average of 10.39 errors; and participants in the single entry condition made an average of 12.03 errors. Thus, visual checking resulted in 29.58 times more errors than double entry. Stated another way, they made 2958% more errors. See Fig. 2.

3.3. Effects on research results

We examined the effect of data entry errors on three statistics: coefficient alpha, the correlation, and the independent samples t -test. For each statistic, we calculated the “true” values of the statistics when the correct data were used (i.e., the data actually given on the data entry sheets)². We then compared these to the “observed” values of the statistics that were calculated using the data entered by participants.

Double entry was much more likely to result in correct values for these statistics than single entry or visual checking (see Fig. 3). For example, 89% of the participants who used double entry obtained correct values for coefficient alpha for all four scales, as

compared to only 34% for visual checking. The chi-squared test of independence showed that these differences were statistically significant ($p < .001$) for all three types of statistic.

Data entry errors sometimes had profound effects on these statistical results. Coefficient alphas were sometimes changed by more than .40 (for example, when the correct value was .67, one observed value was .24). Correlations were sometimes reduced to nearly zero (for example, when the correct correlation was .41, one observed correlation was .12). Significant t -tests sometimes became non-significant (for example, when the correct result was $t\text{-obs} = 3.13, p < .01$, one observed result was $t\text{-obs} = 1.73, p > .05$) and non-significant t -tests sometimes became significant (for example, when the correct result was $t\text{-obs} = 2.04, p > .05$, one observed result was $t\text{-obs} = 2.64, p < .05$). If these participants had been research assistants who were entering data for a real study, then the published conclusions for that study would be substantially wrong.

3.4. Detection and correction of errors

Further examination of the data showed that most of the data entry errors that participants made would be hard to detect. The 195 participants made a total of 1485 errors. Only 85 (0.06%) of these errors could have been detected by a systematic examination of histograms or frequency tables. 57 of the errors consisted of entering a value that was outside the allowable range for the variable (for example, on a scale where the maximum value was 3, participants sometimes entered the number 4). Another 28 of these errors consisted of leaving a variable blank. The remaining 1400 er-

² Originally, the data sheets for this study were randomly created. This resulted in coefficient alphas, correlations, and group differences that were close to zero. Therefore, short forms of each test were deliberately constructed to maximize the statistics being examined. These short forms resulted in realistic values of coefficient alpha and t -observed for all four tests but only two realistic correlations; thus we compared “observed” to “true” correlations only for those two pairs of variables.

rors would have been difficult to detect and would not have been noticeable from histograms or frequency tables.

4. Discussion

Data entry errors introduce another source of random error into our experiments. At the least, these errors reduce reliability, effect sizes, and statistical power, making significant findings less likely. At the worst, they can completely invalidate a statistical analysis. Because of this, researchers must work diligently to prevent, identify, and correct data entry errors. Researchers use corrective efforts such as diagnostic statistics to identify unusual values and use advanced statistical techniques that may be less sensitive to outliers. But these techniques do not identify the relatively common errors that are within the allowable range for the variables. It is more effective to design a human-computer interaction that will result in few data entry errors in the first place.

Some data entry methods are better than others. Double entry resulted in significantly fewer errors than both visual checking and single entry. The differences between these techniques were large: Participants using visual checking made 295% more errors than those using double entry; and only 17.1% of the visual checking participants had perfect accuracy, as compared to 77.4% of the double entry participants. These data entry errors sometimes had substantial effects on the statistics that were calculated based upon the data participants entered. Finally, the vast majority of errors were within the allowable range for the variables, so that they would be undetectable with frequency tables and histograms. Double entry took 33% longer than visual checking, but we conclude that the substantial increase in accuracy is worth the additional time. In contrast, visual checking was not significantly more accurate than single entry ($p = .843$), despite the extra time involved.

Researchers should not use data entry systems that are known to reduce data quality and invalidate statistical findings. Therefore, single entry and visual checking by a single person should be abandoned. Studies that have examined data quality (Kawado et al., 2003; Reynolds-Haertle & McBride, 1992; and this study) have consistently found that double entry systems are the most accurate. Future research should examine the effectiveness of additional data entry systems, such as visual checking that is completed by pairs of people. In the meantime, researchers should use data entry systems that we know produce accurate data and accurate research conclusions. Commercial double entry systems are available from SPSS and SAS, and free double entry systems are available as stand alone programs (Lauritsen & Bruus, 2008), Internet-based systems (Harris et al., 2009), or as free add-ons for Microsoft Access (Beatty, 1999) and Microsoft Excel (Barchard & Pace, 2008, 2010).

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Appendix A. Example data sheet

The Social Skills Study										ID: 101		
Sex:	M	F										
	Family Background						School Experiences					
1.	(SD)	D	N	A	SA		1.	D	N	(A)		
2.	(SD)	D	N	A	SA		2.	D	(N)	A		
3.	SD	D	N	A	(SA)		3.	(D)	N	A		
4.	SD	D	N	(A)	SA		4.	D	N	(A)		
5.	SD	D	(N)	A	SA		5.	D	(N)	A		
6.	SD	(D)	N	A	SA		6.	D	N	(A)		
7.	SD	D	(N)	A	SA		7.	(D)	N	A		
8.	SD	D	(N)	A	SA		8.	D	N	(A)		
9.	(SD)	D	N	A	SA		9.	D	(N)	A		
10.	(SD)	D	N	A	SA		10.	(D)	N	A		
	Extraversion						Social Skills Test					
1.	1	2	3	4	5		1.	1	2	(3)		
2.	1	2	3	4	(5)		2.	(1)	2	3		
3.	1	2	(3)	4	5		3.	1	(2)	3		
4.	1	(2)	3	4	5		4.	1	(2)	3		
5.	1	(2)	3	4	5		5.	(1)	2	3		
6.	1	2	3	4	(5)		6.	1	(2)	3		
7.	1	2	(3)	4	5		7.	(1)	2	3		
8.	1	2	(3)	4	5		8.	(1)	2	3		
9.	1	(2)	3	4	5		9.	1	(2)	3		
10.	1	(2)	3	4	5		10.	(1)	2	3		

References

- Barchard, K. A., & Pace, L. A. (2010). Poka-Yoke Data Entry System Version 1.18. Excel file that shows how to set up a double-entry data entry system for any number of measures and items. <barchard@unlv.nevada.edu>.
- Barchard, K. A., & Pace, L. A. (2008). Meeting the challenge of high quality data entry: A free double-entry system. *International Journal of Services and Standards*, 4, 359–376. doi:[10.1504/IJSS.2008.020053](https://doi.org/10.1504/IJSS.2008.020053).
- Beatty, J. C. (1999). The PowerChecker: A Visual Basic program for ensuring data integrity. *Behavior, Research Methods, Innovation, & Computers*, 31, 737–740.
- Bollen, K. A. (1987). Outliers and improper solutions. *Sociological Methods & Research*, 15(4), 375–384.
- Burchinal, M., & Neebe, E. (2006). Data management: Recommended practices. *Monographs of the Society for Research in Child Development*, 71, 9–23. doi:[10.1111/j.1540-5834.2006.00354.x](https://doi.org/10.1111/j.1540-5834.2006.00354.x).
- Cameron, A., Ewen, M., Ross-Degnan, D., Ball, D., & Laing, R. (2008). Medicine prices, availability, and affordability in 36 developing and middle-income countries: A secondary analysis. *The Lancet*, doi:[10.1016/S0140-6736.240-249](https://doi.org/10.1016/S0140-6736.240-249).
- Cummings, J., & Masten, J. (1994). Customized dual data entry for computerized data analysis. *Quality Assurance*, 3, 300–303.

- Harris, P. A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., & Conde, J. G. (2009). Research electronic data capture (REDCap) – A metadata-driven methodology and workflow process for providing translational research informatics support. *Journal of Biomedical Informatics*, 42(2), 377–381.
- Howard, W. (1976). Robust statistics: A survey and some prescriptions. *Journal of Educational Statistics*, 1(4), 285–312. doi:10.2307/1164985.
- Kawado, M., Hinotsu, S., Matsuyama, Y., Yamaguchi, T., Hashimoto, S., & Ohashi, Y. (2003). A comparison of error detection rates between the reading aloud method and the double data entry method. *Controlled Clinical Trials*, doi:10.1016/S0197-2456.0300569.
- Kruskal, W. H. (1960). Some remarks on wild observations. *Technometrics*, 2, doi:10.2307/1266526. <<http://www.tufts.edu/~gdallal/out.htm>>. Accessed 29.11.10.
- Kulinskaya, E., & Staudte, R. G. (2006). Interval estimates of weighted effect sizes in the one-way heteroscedastic ANOVA. *British Journal of Mathematical and Statistical Psychology*, 59(1), 97–111. doi:10.1348/000711005X68174.
- Lauritsen, J. M., & Bruus, M. (2008). EpiData Entry (version v2.1). A comprehensive tool for validated entry and documentation of data. Odense, Denmark: The EpiData Association. <<http://www.epidata.dk>>. Accessed 29.11.10.
- Liu, Y., Wu, A. D., & Zumbo, B. D. (2010). The impact of outliers on Cronbach's coefficient alpha estimate of reliability: Ordinal/rating scale item responses. *Educational and Psychological Measurement*, 70(1), 5–21. doi:10.1177/0013164409344548.
- Mavridis, D., & Moustaki, I. (2008). Detecting outliers in factor analysis using the forward search algorithm. *Multivariate Behavioral Research*, 43(3), 453–475. doi:10.1080/00273170802285909.
- Reynolds-Haertle, R. A., & McBride, R., (1992). Single versus double data entry in CAST Controlled Clinical Trials, 13, 487–494. doi:10.1016/0197-2456(92)90205-E
- Tukey, J. W. (1977). *Exploratory data analysis*. Reading, MA: Addison-Wesley.
- Velleman, D. C., & Hoaglin, P. F. (1995). A critical look at some analyses of major league baseball salaries. *American Statistician*, 49, 277–285. doi:10.2307/2684201.
- Wilcox, R. R. (1998). How many discoveries have been lost by ignoring modern statistical methods. *American Psychologist*, 53, 300–314. doi:10.1037/0003-066X.53.3.300.
- Wilcox, R. R. (2008). Robust principal components: A generalized variance perspective. *Behavior Research Methods*, 40(1), 102–108. doi:10.3758/BRM.40.1.102.
- Winkler, W. E. (2004). Methods for evaluating and creating quality data. *Information Systems*, 29, 531–550. doi:10.1016/j.is.2003.12.003.
- Yan, L., & Zumbo, B. D. (2007). The impact of outliers on Cronbach's coefficient alpha estimate of reliability: Visual analogue scales. *Educational & Psychological Measurement*, 67(4), 620–634. doi:10.1111/j.0013164406296976.
- Ye-Mao, X., Xin-Yuan, S., & Sik-Yum, L. (2009). Robust model fitting for the non-linear structural equation model under normal theory. *British Journal of Mathematical & Statistical Psychology*, 62(3), 529–568. doi:10.1348/000711008X345966.
- Yuan, K.-H., & Zhong, X. (2008). Outliers, leverage observation, and influential cases in factor analysis: Using robust procedures to minimize their effect. *Sociological Methodology*, 38(1), 329–368.