Determining Sample Size for Research Activities: The Case of Organizational Research

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Abstract

Sample size determination is often an important step and decision that educational and organizational researchers are facing. The quality and precision of research is being influenced by inadequate, excessive or inappropriate sample sizes. Selecting the sample size for a study requires compromise between balancing the need for statistical power, economy and timeliness. There is a temptation for the researchers to take some short cuts. The paper describes the importance and procedure of determining sample size for continuous and categorical variables using Cochran's (1977) formula. The paper illustrates the usage of sample sizes formula, including the formula for adjusting for Cochran's (1977) correction when the sample size exceeds 5% of the population. Tables are included to help researchers in determining the sample size for a research problem based on any three alpha levels and a set of standard error rate for categorical and continuous data. Procedures for determining the appropriate sample size for multiple regression, factor analysis and structural equation modeling are discussed. Common issues in sample size determination are examined. Non-respondent sampling issues are also addressed.

Keywords: Sample size; Organizational research; Sampling; Research method

1 Introduction

The increasing demand for organizational research in the area of education and management has created the need for an efficient method of determining the sample size. Sample size is an important feature of any empirical study needed to be representative of a given population with the intention of making inferences about the population on the basis of the sample characteristics. A common goal of the educational, organizational or management research is to collect data representative of a population. The researchers will calculate the statistics that describe the sample and use those statistics to make inferences about the population parameters of the target population.

In order to achieve the desired outcome, sampling design is required. Sampling design begins by defining the target population in terms of elements, sampling frame and sampling units. Sampling frame is a representative of the elements of the target population. However, getting the most current sampling frame is crucial. An obsolete sampling frame will result in obtaining an under-coverage sample. The next step involves selecting a sampling technique and determining the sample size. However, the criteria of determining sample size are subject to several qualitative factors such as the dispersion of the data or the heterogeneity of the population, the confidence level or the level of precision of the estimates, the error range and the number of subgroups. The sample sizes increase with the increase in the population variability, degree of confidence and the precision level required of the estimate (Malhotra, 2010). As sample size is directly proportional to population variability, a bigger sample is required for heterogeneous population. The variability of the characteristics in the population enters into the sample size calculation by way of population variance or sample variance. However, when critiquing business research, (Blair & Zinkhan, 2006; Groves & Peytcheva, 2008; Wunsch, 1986) it was stated that two of the most consistent flaws in sampling are (i) disregard of the sampling error when determining the sample size, and (ii) disregard for response and non-response bias. However, in implementing a quantitative survey design, sampling error and dealing with non-response bias are essential. Non-response distorts the result of many surveys, even surveys that are carefully designed.

One of the real advantages of quantitative methods is their ability to use smaller groups of people as a sample to make inferences about larger groups that would be prohibitively expensive to study. The question then is how large of a sample is required to infer research findings back to a population? Another issue is how should the selection process be so as the sample selected would be representative of the population? The issue is particularly pertinent when the subjects of the sample are heterogeneous. A large unrepresentative sample may do more damage than a small one. Many people think that large samples are always better than small ones. The design of the sample is far more important than the absolute size of the sample.

2 Sample Size Planning

Statistical studies (surveys, experiments, observational studies, etc.) are always better when they are carefully planned. Good planning covers many aspects such as the problems should be carefully defined and operationalized. Observational or survey units should be selected from appropriate population. The studies need to be randomized correctly while the procedures should be followed carefully. Reliable instruments should be used to obtain measurements. The study must be of adequate size relative to the goals of the study. It should be big enough that an effect of such magnitude as to be of scientific significance will also be statistically significant.

Sample size is important for economic reasons. An undersized study can be a waste of resources for not having the capability to produce useful results. On the other hand, an oversized study can use more resources than necessary. In an experiment involving human or animal subjects, sample size is a pivotal issue for ethical reasons. There are numerous articles especially in biostatistics journals concerning sample size determination for specific tests. Another interest, are studies of the extent to which sample size is adequate or inadequate in published studies. Furthermore, there is a growing amount of software for sample size determination. The researcher can specify the desired width of confidence and determine the sample size to achieve that goal. One of the most popular approaches to sample size determination involves studying the power of a test of hypothesis. The power approach involves the element of specifying a hypothesis test on a parameter θ, specifying the significance level α of the test, and specifying the effect size $\bar{\theta}$.

The paper will describe common procedures for determining sample size. The discussion of this paper is guided by the appropriate use of Cochran's (1977) sample size formula for both continuous and categorical data. Krejcie and Morgan's (1970) formula for determining sample size for categorical data will be briefly discussed because it provides identical sample sizes in all cases where the researcher adjusts the *t* value used based on the population size, which is required when the population size is 120 or less. Likewise, researchers should be cautious when using any of the widely circulated sample size tables based on Krejcie and Morgan's (1970) formula, as they assume an alpha of .05 and a degree of accuracy of .05 for categorical data and .03 for continuous data. Other formulas are available; however, these two formulas are used more than any others.

3 Sample Size Determination

3.1 Primary Variables of Measurement

Several qualitative factors should be taken into consideration when determining the sample size. These include the importance of the decisions, the nature of the research, the number of variables, the nature of the variables, the nature of the analysis, sampled size used in similar studies, incidence rates, completion rates, and resources constraints. The statistically determined sample size is the net or final sample size. The sample size is determined after eliminating potential respondents who do not qualify or who do not complete the interview or the questionnaire. The initial sample size has to be larger or over sampled to offset problems such as unexpected completion rates of the survey.

The researcher should decide as to which variables will be incorporated in the formula calculation. For example, if the researcher plans to use a seven-point Likert scale to measure a continuous variable, e.g. job satisfaction or organizational commitment and also plans to determine if respondents differ by certain categorical variables, e.g. gender, permanent position, education level, job experience, hierarchy of jobs, etc. which variables should be used as the basis for the sample size calculation? This is important because the use of gender (categorical) as the primary variable will result in a substantial larger sample size than if one used the seven-point scale (continuous) as the primary variable of measure (refer Table 1).

Table 1. Determining Minimum Returned Sample Size for a Given Population Size for Continuous and Categorical Data

Population	Sample Size					
	Continuous Data (Margin of Error=.03)			Categorical Data (Margin of Error = .05)		
	Alpha = .10 t = 1.65	Alpha=.05 t = 1.96	Alpha = .01 t = 2.58	P = .05 t = 1.65	P = .05 t = 1.96	P =.05 t = 2.58
100	46	55	68	74	80	87
200	59	75	102	116	132	154
300	65	85	123	143	169	207
400	69	92	137	162	196	250
500	72	96	147	176	218	286
600	73	100	155	187	235	316
700	75	102	161	196	249	341
800	76	104	166	203	260	363
900	76	105	170	209	270	382
1,000	77	106	173	213	278	399
1,500	83	110	183	230	306	461
2,000	83	112	189	239	323	499
4,000	83	119	198	254	354	570
6,000	83	119	209	259	362	598
8,000	83	119	209	262	367	613
10,000	83	119	209	264	370	623

Note: The margin of error used in the table was .03 for continuous data and .05 for categorical data.

One method of determining sample size is to specify margin of errors for the items. It is regarded as the most vital element to the survey. An estimation of the sample size needed is first made separately for each of these important items. When calculations are completed, the researcher will have a range of n's usually ranging from smaller *n*'s for scaled, continuous variables, to larger *n*'s for dichotomous or categorical variables. The researcher should make sampling decisions based on these data. If the *n*'s for variables of interest are relatively close, the researcher can simply use the largest *n* as the sample size and be confident that the sample size will provide the desired results.

More commonly, there is a sufficient variation among the *n*'s so that we are reluctant to choose the largest, either from budgetary considerations or because this will give an over-all standard of precision substantially higher than originally contemplated. In this event, the desired standard of precision may be relaxed for certain of the items, in order to permit the use of smaller value of *n*. The researcher may also decide to use this information in deciding whether to keep all of the variables identified in the study. "In some cases, the *n*'s are so discordant that some of them must be dropped from the inquiry; ….." (Cochran, 1977).

3.2 Factors in Determining Sample Size

Three factors are required to specify sample size: (i) the heterogeneity (i.e. variance) of the population; (ii) magnitude of acceptable error (i.e. + or - of some amount say 3 percent or 5 percent) or the level of precision, and (iii) confidence intervals (i.e., 90 percent, 95 percent, 99 percent). The determination of sample size heavily depends on variability (i.e. variance) or heterogeneity within the population.

3.3 Error Estimation

Cochran's (1977) formula uses two key factors: (i) the risk the researcher is willing to accept in the study, commonly called margin of error or the error the researcher is willing to accept; and (ii) the alpha level, the level of acceptable risk the researcher is willing to accept that the true margin for error exceeds the acceptable margin of error; i.e., the probability that differences revealed by statistical analyses really do not exist; also known as Type I error. Another type of error, namely Type II error, also known as Beta error will not be addressed here. Type II error occurs when statistical procedures result in a judgment of no significant differences when these differences do indeed exist.

3.4 Alpha Level

The alpha level used in determining sample size in most management or educational research studies is either .05 or .01 (Ary, Jacobs, & Razavieh, 1996). In Cochran's formula, the alpha level is incorporated into the formula by utilizing the t-value for the alpha level selected (e.g., t-value for alpha level of .05 is 1.96 for the sample size of above 120). Researchers should ensure that they use the correct t value when their research involves smaller populations, e.g. t-value for alpha of .05 and a population of 60 is 2.00 and for a population of 30, t-value value for alpha of .o5 is 2.04. In general, an alpha level of .05 is acceptable for most research. An alpha level of .10 or lower may be used if the researcher is more interested in identifying marginal relationships, differences or other statistical phenomena as a precursor to further studies. An alpha level of .01 may be used in those cases where decisions based on the research are critical and errors may cause substantial financial or personal harm, e.g., major programmatic changes.

3.5 Acceptable Margin of Error

The general rule relative to acceptable margins of error in educational, management and social research is as follows: for categorical data, the acceptable margin of error is 5% and, for continuous data, 3% margin of error is acceptable (Krejcie & Morgan, 1970). For example, a 3% margin of error would result in the researcher being confident that the true mean of seven point scale is within $\pm$.21 (.03 times seven points on the scale) of the mean calculated from the research sample. For a dichotomous variable, a 5% margin of error would result in the researcher being confident that the proportion of respondents who were male was within $\pm$5% of the population calculated from the research sample. Researchers may increase these values when a higher margin of error is acceptable or may decrease these values when a higher degree of precision is needed.

3.6 Variance Estimation

A critical component of sample size formulas is the estimation of variance in the primary variables of interest in the study. The researcher does not have direct control over variance and must incorporate variance estimates into the research design. Cochran (1977) listed four ways of estimating population variances for sample size determinations: (i) take the sample size in two steps, and use the results of the first step to determine how many additional responses are needed to attain an appropriate sample size based on the variance observed in the first step data; (ii) use pilot study results; (iii) use data from previous studies of the same or similar population; or (iv) estimate or guess the structure of the population assisted by some logical mathematical results. The first three ways are logical and procedure valid estimates of variance. Therefore they do not need to be discussed further. However, in many educational, managements and social research studies, it is not feasible to use any of the first three ways and the researcher should estimate variance using the fourth method.

A researcher needs to estimate the variance of scaled and categorical variables. To estimate the variance of scaled variable, one must determine the inclusive range of the scale, and then divide by the number of standard deviations that would include all possible values in the range, and then square this number. For example, if a researcher used a seven point scale using Likert scale or Semantic differential, and given that six standard deviations (area under a curve with three to each side of the mean) would capture 98% of the responses, the calculation would be as follows:

$$s = \frac{7 \text{ (number of points on the scale)}}{6 \text{ (number of standard deviations)}} = 1.167$$

Krejcie Maoran (1970) also recommended that the researcher use .50 as the level of precision as an estimate of the population proportion. The proportion will result in the maximization of variance, which will produce the maximum sample size. This proportion can be used to estimate variance in the population. By squaring .50 it will result in a population variance estimate of .25 for a dichotomous variable.

4 Computation of Sample Size

In the business world, samples are determined prior to data collection to ensure that confidence interval is narrow enough to be useful in making decisions. Determining the proper sample size is a complicated procedure, subject to constraints of budget, time and the amount of acceptable sampling error. To develop an equation for determining the appropriate sample size needed when constructing a confidence interval estimate for the mean is:

$$\bar{X} \pm Z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \rightarrow \bar{X} + e$$

The amount added to or subtracted from $\bar{X}$ is equal to half the width of the interval. This quantity represents the amount of imprecision in the estimate that results from sampling error. The sampling error e is defined as:

$$e = Z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$$

Solving for n gives the sample size needed to construct the appropriate confidence interval for the estimate for the mean. The sample size, n is equal to the product of $Z_{\alpha/2}$ value squared and the standard deviation σ squared divided by the square of the sampling error e.

$$n = \frac{Z_{\alpha/2}^2 \sigma^2}{e^2} or \left(\frac{z\sigma}{e} \right)^2$$

To compute the sample size, we must know three quantities:

- The desired confidence level, which determines the value of $Z_{\alpha/2}$
- The acceptable sampling error*, e*
- The standard deviation, σ

We plug our desired precision ε and the appropriate z for the desired confidence interval. However, σ poses a problem since it is usually unknown. Several ways were proposed to appropriate the value of σ.

Method 1: Take a small sample and use the sample estimate s in place of σ. This method is the most common practice among researchers.

Method 2: Estimate upper and lower limits *a* and *b* and set $\sigma = \left[(b-a)^2 / 12 \right]^{1/2}$. For example we might guess the weight of a light duty truck to range from 1,500 kilos to 3,500 kilos implying a standard deviation of $\sigma = \left[(3,500 - 1,500)^2 / 12 \right]^{1/2} = 577$ kilos. Since a uniform distribution has no central tendency, the actual σ is probably smaller than our guess.

Method 3: Estimate the upper and lower bound *a* and *b,* and set $\sigma = (b-a)/6.$ This assumes normality with most of the data within $\mu + 3\sigma$ and $\mu - 3\sigma$ so the range is 6σ. For example we might guess the weight of a light truck is from 1,500 kilos to 3,500 kilos implying σ =(3,500 -1,500)/6 = 333 kilos. The estimate of σ is based on the empirical rule.

4.1 Sample Size Determination of Continuous Data

In calculating the sample size for a continuous data, the researcher has set an alpha level a priori at .05 levels for a seven point scale, and has set the level of acceptable error at 3% and has estimated the standard deviations of the scale as 1.167. Cochran's sample size formula for continuous data and an example of its use is presented here along with the explanations as to how these decisions were made.

$$n_o = \frac{(t)^2 \times (s)^2}{(d)^2} = \frac{(1.96)^2(1,679)^2}{(7 \times .03)^2} = 118$$

Where t = value for selected alpha level of .025 in each tail = 1.96 when n is greater than 120 (the alpha level of .05 indicates the level of risks the researcher is willing to take that true margin of error may exceed the acceptable margin of error).

Where s = estimate of standard deviation in the population = 1.167 (estimate of variance deviation for 7 point scale calculated by using 7 [inclusive range of scale] divided by 6 [number of standard deviations that include almost all (approximately 98%) of the possible values in the range).

Where d = acceptable margin of error for mean being estimated = .21 (number of points on primary scale * acceptable margin of error; points on primary scale = 7; acceptable margin of error = .03[error that the researcher is willing to accept]).

Therefore, for a population of 1,679, the required sample size is 118. However, since the sample size exceeds 5% of the population (1.679 * .05 = 84), Cochran's (1977) correction formula will be used to calculate the final sample size. These calculations are as follows:

$$n_1 = \frac{n_o}{(1 + n_o / population)} = \frac{(118)}{(1 + 118/1679)} = 111$$

Where population size = 1,679

Where n_o = required return sample size according to Cochran's formula= 118.

n_1 = required return sample size because sample > 5% of population.

These procedures result in the minimum required sample size. If a researcher has a captive audience, this sample size may be attained easily. However, since many educational, management and social research studies often use data collection methods such as surveys and other voluntary participation methods, the responses rate are well below 100%. Salkind (1997) recommended oversampling if the researcher is mailing out surveys or questionnaires. The researcher should increase the sample size by 40% - 50% to account for lost mail and uncooperative subjects. Fink (1995) stated that oversampling can add costs to the survey but is often necessary. Cochran (1977) stated that a second consequence is, of course, that the variances of estimates are increased because the sample actually obtained is smaller than the target sample. This factor can be allowed for, at least approximately, in selecting the size of the sample. However, many researchers criticize the use of over-sampling to ensure that this minimum sample size is achieved and suggestions on how to secure the minimal sample size are scarce.

Most researchers decide to use oversampling as the response rate is low especially using survey research. A researcher may be able to consult other researchers or review the research literature in similar fields to determine the response rates that have been achieved with similar, and if necessary, dissimilar populations. The estimated response rate can be based on priori research experience. If it was anticipated that a respond rate of 55% would be achieved, given a required minimum sample size of 111, the sample size required to produce the minimum sample size would be:

The anticipated return rate = 55%

Where n_2 = sample size adjusted for response rate

Minimum sample size corrected = 111

Therefore, n_2 = 111/.55 = 202.

4.2 Sample Size for Categorical Data

The sample size formulas and procedures used for categorical data are similar, with some modification and variation. With an alpha level of .05 set based on a priori by the researcher, and the level of acceptable error is set 5% and has estimated the standard deviation of the scale as .5. Cochran's sample size formula for categorical data and an example of its use is presented as:

$$n_o = \frac{(t)^2 \times (p)(q)}{(d)^2} = \frac{(1.96)^2 (.5)(.5)}{(.05)^2} = 384$$

Where t = value of selected alpha level of .025 in each tail = 1.96 (the alpha level of .05 indicates the level of risk the researcher is willing to take as the true margin of error may exceed the acceptable margin of error).
Where (p)(q) = estimate of variance = .25 (maximum possible proportion (.5) * (1-.5)- maximum possible proportion (.5) produces maximum possible sample size).
Where d = acceptable margin of error for proportion being estimated = .05 (error researcher is willing to accept).

Some text books provide a formula based on the z value associated with the confidence level. The sample size using the standard error for proportion is as follows:

$$n_1 = \frac{\pi(1-\pi)z^2}{D^2} = \frac{0.5(1-0.5)(1.96)^2}{(.05)^2} = \frac{0.5(0.5)(1.96)^2}{(.05)^2} = 384$$

Therefore, for a population of 1,679, the required sample size is 384. However, since the sample size exceeds 5% of the population (1,679 x .05 = 84), Cochran's (1977) correction formula should be used to calculate the final sample size. The calculation is as follows:

$$n_1 = \frac{n_o}{\left(1 + n_o / population\right)} = \frac{(384)}{\left(1 + 384/1679\right)} = 313$$

Where population size = 1,679

Where n_o = required return sample according to Cochran's formula =384

Where n_1 = required return sample size because sample > 5% of the population.

These procedures result in a minimum returned sample size of 313. Using the same oversampling procedures as cited in the continuous data example, and again assuming a response rate of 55%, a minimum drawn sample size of 482 should be used. These calculations were based on the following:

Where anticipated return rate = 55%

Where no = sample size adjusted for response rate

Where minimum sample size (corrected) = 313

Therefore, n_2 = 313/ .55 = 482.

If the researcher wants to increase the level of confidence for example to 99 percent, this will require a larger sample. The z value corresponding to 99 percent level of confidence is 2.58. The sample size would be:

$$n_o = \frac{(t)^2 \times (p)(q)}{(d)^2} = \frac{(2.58)^2(.5)(.5)}{(.05)^2} = 665.64$$

As the sample size exceeds 5% of the population (1,679 x .05 = 84), Cochran's (1977) correction formula should be used to calculate the final sample size. The calculation is as follows:

$$n_1 = \frac{n_o}{\left(1 + n_o / population\right)} = \frac{(666)}{\left(1 + 666/1679\right)} = 477$$

The sample size corresponding to 99 percent confidence level should be 666. Observe how much the change in the confidence level changed the size of the sample. An increase from 95 percent to 99 percent level of confidence resulted in an increase of 281 observations or 73 percent $\left[\left(666/385\right)\times 100\right]$. This would increase the cost of the study, both in terms of time and money. Hence, the level of confidence should be considered carefully. Following the same oversampling procedures as cited in the continuous data example, and again assuming a response rate of 55%, a minimum drawn sample size of 477/.55 = 868 should be used.

4.3 Alternative Method of Calculation for Categorical Data

Krejcie and Morgan (1970) introduced alternative formula in computing sample size for categorical data based on the formula below:

$$s = \chi^2 NP(1-P) / d^2(N-1) + \chi^2 P(1-P)$$

or

$$s = \frac{\chi^2 NP(1-P)}{d^2(N-1) + \chi^2 P(1-P)}$$

Where s = required sample size

χ^2 = the table value of chi-square for 1 degree of freedom at the desired confidence level of .05= (3.841)

N = the population size

P = the population proportion (assumed to be .05 since this would provide maximum sample size

d = the degree of accuracy expressed as a proportion (.05).

4.4 Sample Size Determination Table

Table 1 presents sample size values that will be appropriate for many common sampling problems. The table includes sample sizes for both continuous and categorical data assuming alpha levels of .10, .05, or .01. The margins of error used in the table were .03 for continuous data and .05 for categorical data. Table 2 presents sample size for categorical data assuming alpha level of .05 and margin of error of .05. Researchers may use the table if the margin of error shown is appropriate for their study; however, the appropriate sample size must be calculated if these error rates are not appropriate.

Table 2. Determining Sample Size from a Given Population for Categorical Data (Margin of error = .05 and P = .05)

N	s	N	S	N	s
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

5 Other Sample Size Determination Considerations

5.1 Regression Analysis

There can be situations where the procedures described in the previous paragraph will not satisfy the needs of a study and examples will be addressed here. One situation is when the researcher wishes to use multiple regression analysis in a study. To use multiple regression analysis, the ratio of observations to independent variables should not fall below five. If this minimum is not followed, there is a risk of over fitting (Hair, Black, Babin,& Anderson, 2010). A more conservative ratio, is ten observations for each independent variable was reported optimal by Miller and Kunce (1973) and Halinski and Felt (1970). However, the required sample size depends on a number of issues such as the desired power, alpha level, number of predictors and expected effect sizes (Tabachnick & Fidell, 2007). Green (1991) provides a thorough discussion of these issues and provides some procedures to help decide how many cases are necessary. Some simple rules of thumb are $N \geq 50 + 8m$ (where m is the number of IVs) for testing multiple correlations and $N \geq 104+6m$ for testing individual predictors. These rules of thumb assume a medium size relationship between the IVs and DV, α=.05 and β=.20. For six predictors, the researcher needs 50 + (8)(6) = 98 cases to test regression model and 104 + (6)(6) = 140 cases for testing individual predictors.

These ratios are especially critical in using regression analyses with continuous data because sample sizes for continuous data are typically much smaller than sample sizes for categorical data. Therefore, there is a possibility that the random sample will not be sufficient if multiple variables are used in the regression analysis. For example, in the continuous data illustration, a population of 1,679 was utilized and it was determined that a minimum returned sample size of 111 was required. The sample size for a population of 1679 in the categorical data example was 313. Table 2 developed based on the recommendations cited in the previous paragraph, uses both the five to one and ten to one ratios.

As shown in Table 2, if the researcher uses optimal ratio of ten to one with continuous data, the number of regressors (independent variables) in the multiple regression model would be limited to 11. Larger numbers of regressors could be used with the other situations shown. It should be noted that if a variable such as ethnicity (dummy variable) is incorporated into the categorical example this variable must be dummy coded, which will result in multiple variables utilized in the model rather than a single variable. In case of ethnicity that has four levels e.g. Bumiputera, Chinese, Indian, and others. Bumiputera would each be coded as 1 = yes and 0 = no for levels of predictors in the regression model, which would result in three variables rather than one in a regression model.

In the continuous data example, if a researcher planned to use 14 variables in a multiple regression analysis and wished to use the optimal ratio of ten to one, the returned sample size must be increased from 111 to 140. This sample size of 140 would be calculated from taking the number of independent variables to be entered in the regression (fourteen) and multiplying them by the number of the ratio (ten). Caution should be taken when making this decision because raising the sample size above the level indicated by the sample size formula will increase the type I error.

5.2 Factor Analysis

In the factor analysis literature much attention has been given to the issue of sample size. It is widely understood that the use of larger samples in applications of factor analysis tends to provide results such that the sample factor loadings provide more precise estimates of population loadings and also are more stable. Despite general agreement on this matter there is considerable divergence of opinion and evidence about the question of how large a sample is necessary to adequately achieve these objectives. Recommendations and findings about this issue are diverse and often contradictory.

A wide range of recommendation regarding sample size in factor analysis has been proposed. These guidelines are stated in terms of minimum necessary sample size, N, or the minimum ratio of N to the number of variables being analyzed. Gorsuch (1983) recommended that N should be at least 100 and Kline (1979) supported this recommendation. Gulford (1954) indicated that N should be at least 200 while Cattell (1978) claimed that the minimum desirable N to be 250. Using the N:p ratio, Cattell (1978) believed this ratio should be in the range of 3 to 6. Gorsuch (1983) argued for a minimum ratio of 5. Everitt (1975) recommended that the N:p ratio should at least be 10. Others say that the same ratio considerations discussed under multiple regressions should be used, with one additional criteria namely, that factor analysis should not be done with less than 50 observations and preferably sample size should be 100 or larger (Hair et al., 2010). A general rule should be the minimum is to have at least five times as many observations as the number of variables to be analyzed. However, the more acceptable sample size would be a 10:1 ratio. Some researchers even propose a minimum of 20 cases for each variable. It should be noted that an increase in sample size will decrease the level at which an item loading on a factor is significant. For example, assuming an alpha level of .05, a factor would have to load at a level of .75 or higher to be significant in a sample size of 50, while a factor would only have to load at a level of .30 to be significant in a sample size of 350 (Hair et al., 2010).

5.3 Structural Equation Modeling

Covariances are less stable when estimating from small samples (Tabachnick & Fidell, 2007). Structural Equation Modeling (SEM) is based on covariance. SEM then, like factor analysis, is grounded in large sample theory. Velicer and Fava (1998) found that in exploratory factor analysis size of the loadings, the number of variables, and the size of the samples were important elements in obtaining a good factor model.

Structural equation modeling (SEM) requires larger samples relative to other multivariate approaches. Some of the statistical algorithms that used SEM were found to be unreliable with small samples. Opinions regarding minimum sample size are varied. However, there are five considerations affecting the required sample size for SEM. They are the following: multivariate normality of the data; estimation technique; model complexity; amount of missing data; and average error variance among the reflective indicators. Mueller (1996) suggested that the ratio number of participants to number of observed variables should be at least 10 to 1. Bollen (1989) recommended a ratio of 3 to 5 participants per estimated parameter, whereas Bentler and Chou (1987) recommended 5 to 10 participants per estimated parameter. Quintana and Maxwell (1999) observed that there is limited consensus for determining the sample size for adequate power. A major aspect of the application of Covariance Structure Modeling (CSM) in SEM is the assessment of goodness of fit of a hypothesized model to sample data. They indicated that some goodness-of-fit indices perform adequately with sample size as small as 100 participants. In general, statistical indices will perform adequately and yield meaningful and interpretable values when the sample size is made up of 200 or more participants. Quintana and Maxwell recommended using Bentler and Chou's 5 to 10 participants per estimated parameter rule for computing sample size.

As the data deviate more from the assumption of multivariate normality, the ratio of respondents to parameters needs to increase. The accepted ratio to minimize problems with deviations from normality is 15 respondents for each parameter estimated in the model. Some estimation procedures are specifically designed to deal with non-normal data, and the researcher is always encouraged to provide sufficient sample size to allow for sampling error's impact to be minimized.

The most common SEM estimation procedure is Maximum Llikelihood Estimation (MLE). MLE requires bigger samples when it is confronted with sampling errors. Hair (2010) recommends a sample size of 200 to provide a sound basis for estimation. However when the sample sizes increase to around 400 or larger, the process becomes more sensitive and any difference is detected making goodness of fit measures suggest poor fit. Thus the suggested sample size should be in the range 100 to 400 subjects. Sample size is also subject to model complexity. Simple models can be tested with smaller samples. However, as the models become more complex with more constructs and more required parameters to be estimated, bigger samples are required. The other reason is when there are constructs having fewer than three measured indicator variables in the model. Bigger samples are also required when the analyses is based on multi-groups. The purpose of the sample size here is to produce more information and greater stability to the model. The larger sample means with less variability will increase the stability in the solution. Thus complex model requires larger samples.

The other is when there are missing data. Missing data complicate the testing of SEM models and use of SEM. This is because the sample size is reduced to some extent from the original number of cases due to missing data. The researcher should plan for an increase of sample size to offset problems of missing data. The other reasons for the need of increasing sample size are when there are communalities. Communalities represent the average amount of variation among the indicator variable explained by the measurement model. Communality plays a critical role. The communality of an item can be directly calculated as the square of the standardized construct loading. Models containing multiple constructs with communalities less than .5 (standardized loading estimates less than .7) require larger sizes for convergence and stability. When communalities are consistently high (probably greater than .6) than the effect of model fit and precision of parameter estimates receives a low weight, thus greatly reducing the impact of sample size and other aspects of design. As communalities become lower, the roles of sample size become more important. With low communalities and a small number of factors, a much larger sample is needed, probably at least 300. Under worst conditions of low communalities and larger number of weakly determined factors requires very large samples well over 500may be required. Sample size is an important consideration in SEM analysis, as low sample size has several consequences including (a) low power to detect significant path coefficients and variances, and (b) instability (sampling error) in the covariance matrix, leading to attenuation of fit indices.

Hair (2010) had suggested the following for the minimum sample sizes based on the complexity of the model and basic measurement model characteristics:

- Minimum sample size of 100 with models containing five or fewer constructs, each with more than 3 items and with high item communalities of .6 or higher;
- Minimum sample size of 150 with models of seven or fewer constructs, modest communalities of .5 and no under identified constructs;
- Minimum sample size of 300 with models with seven or fewer constructs, lower communalities below .45 and multiple under identified constructs;
- Minimum sample of 500 for models with larger numbers of constructs some with lower communalities and having fewer than three measured items.

Sampling non-respondents: Donald (1967), Hagbert (1968), Johnson (1959), and Miller and Smith (1983) recommended that the researcher take a random sample of 10-20% of non-respondents to use in non-respondent follow-up analyses. If non respondents are treated as a potentially different population, it does not appear to this recommendation as valid or adequate. Rather, the researcher could consider using Cochran's formula to determine an adequate sample of non-respondents for the non-respondent follow-up response analyses.

Budget, time and other constraints: Often the researcher is faced with various constraints that may force him or her to use inadequate sample sizes because of practical versus statistical reasons. These constraints may include budget, time, personnel, and other resource limitations. In these cases, researchers should report both the appropriate sample sizes along with the sample sizes actually used in the study. The reasons for using inadequate sample size and a discussion of the effect on the inadequate sample sizes may influence the results of the study. The researcher should exercise caution when making programmatic recommendations based on research conducted with an adequate sample sizes.

6 Nonresponse Issues in Sampling

The two major non-response issues in sampling are improving response rate and adjusting for non-response. Non-response error arises as some of the potential respondents included in the sample do not respond. This is one of the most significant problems in a survey. The situation is further exacerbated by non-respondents who differ from respondents in terms of demographic, psychographic, personality, attitudinal, motivational and behavioural variables. If the non-respondents differ from the respondents on the characteristics of interest in the survey, the sample estimate will be seriously biased (Malhotra, 2010). Further, the response rate may not be an adequate indicator of non-response bias. Response rate itself does not indicate whether the respondents are representative of the original sample (Heerwegh, 2005). Increasing the response rate may not reduce the response bias if the additional respondents are not different from those that already responded but differ from those who still do not respond (Colombo, 2000).

Survey researchers should distinguish between unit non-response and item non response. Unit non-response is when a person cannot or refuses to be interviewed or answer the questionnaires while item non response is when a respondent does not answer a particular question. The reasons for unit non-response are due to inability to contact the respondents, respondents' refusal to participate, and participants' inability to participate as they may be ill. Often non-respondents differ critically from respondents, but the extent of that difference is unknown unless we can later obtain information about the non-respondents. Given the differences between responders and non-responders that the paper indicates, researchers should attempt to lower refusal rates. This can be done by prior notification, motivating the respondents, giving incentives, good questionnaire design and administration and follow up. Item non-response means that the person does not respond to a particular item on the questionnaire.

7 Conclusion

It is not unusual for researchers to have different opinions as to how sample sizes should be calculated and the procedures used. This will allow the reader to make his or her own judgment as whether to accept the researcher's assumptions and procedures. In general, a researcher could use the standard factor identified in this paper in the sample size determination process.

Another issue is that many studies conducted with entire population census data could and probably should have used samples instead. Many of the studies based on population census data achieved low response rates. Using adequate sample along with high quality data collection efforts will result in more reliable, valid, and generalizable results. It could also result in other resource savings.

The bottom line is simple: research studies take substantial time and effort on the part of the researchers. This paper was designed as a tool that a researcher could use in planning and conducting quality research. When selecting an appropriate sample size for a study is relatively easy, why would not a researcher want to do it right?

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