JOURNAL OF EDUCATION AND INNOVATION

Academic Article

SAMPLE SIZE DETERMINATION TECHNIQUES FOR MULTIVARIATE BEHAVIORAL SCIENCES RESEARCH EMPHASIZING SEM

Received: January 4, 2024 **Revised:** March 25, 2024 **Accepted:** March 25, 2024

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Abstract

The most frequently asked question concerning sampling for multivariate behavioral sciences research is, "What sample size do researcher need?" The answer to this question is influenced by a number of factors, including the purpose of the study, population size, analysis technique, error, the risk of selecting a "bad" sample size, and the sample size for estimate error. Interested readers may obtain a more detailed discussion of the purpose of the study and population size in Sampling. This paper reviews criteria for specifying a sample size for multivariate behavioral sciences research and presents several strategies for determining the sample size for multivariate behavioral sciences research. The conclusion of this article proposes a method for determining the appropriate sample size for multivariate behavioral sciences research. It suggests the following guide: 50: very poor 100: poor 200: fair 300: good 500: very good 1000: excellent 1200: exceptional 1500: profound. Determining the appropriate the sample size for multivariate behavioral sciences research consisting of two conditions which are (1) The condition for the parameters of various statistical techniques such as EFA, CFA, SEM, MSEM, etc. and (2) The second is the condition of the population representative. The sample size must be sufficient for the generalized to the population. If considered through the first conditions, the researchers must consider the minimum sufficiency in the second condition.

Keyword: Research Methodology, Factor Analysis, Structural Equation Modeling, SEM

Introduction

The 21st century is time a revolutionary period for the human behavioral sciences. We have learned a lot about the biological and systems that it is just as important to understand how human behavior and society affect. What is Behavioral and Social Sciences Research? Behavioral is a term that covers a lot of ground. It refers to what people do, as well as what drives them to do things, and it involves psychological processes like emotion. "Social," on the other hand, reflects how individuals interact with each other: in small groups, families, and communities, as well as within populations and in society. Behavioral and social sciences research helps predict, prevent, and manage illness in individuals and in whole populations. This research also helps people change their behaviors, understand treatments, and learn how to stick with them. (National Institute of Health [NIH], 2021, p.1) In behavioral science research, SEM is particularly valuable because it can accommodate the complexity of human behavior and the multitude of factors that influence it. By incorporating latent variables, which are unobserved constructs that underlie observable behaviors, SEM enables researchers to model complex theoretical frameworks and test hypotheses that involve multiple variables and their interrelationships. SEM can be applied in various areas of behavioral science, including psychology, sociology, education, and economics, among others. Researchers use SEM to analyze and validate theoretical models, evaluate the goodness-of-fit of their models to the data, estimate parameters such as regression coefficients and factor loadings, and assess mediation and moderation effects. Overall, SEM provides behavioral scientists with a powerful tool to investigate intricate relationships among variables, offering insights into the underlying mechanisms driving human behavior and contributing to the advancement of knowledge in the field.

Research on behavioral science has a variety of methods. Because the methods used in scientific research are not the only ones available for answering questions, and they are not necessarily the most efficient. There are many different ways of knowing or finding answers to questions. In general, the different ways that people know, or the methods that people use to discover answers, are referred to as methods of acquiring knowledge. (Gravetter, 2018, p. 2) Method of tenacity, method of intuition, method of authority, method of faith, rational method, empirical method, are different ways of acquiring knowledge. (Gravetter, 2018, pp. 3-9) However the power of the scientific approach can be seen all around us. Whether look at biology, chemistry, medicine, physics, anthropology, or psychology, will see amazing advances over the past 5, 25, 50, or 100 years have a greater understanding of the world around us, and the applications of that understanding have kept pace. Goals of behavioral sciences research has four general goals (1) to describe behavior, (2) to predict behavior, (3) to determine the causes of behavior, and (4) to understand or explain behavior based on scientific methods. (Cozby & Bates, 2018, pp. 31-34)

At present behavioral sciences research has the characteristics of the study of human behavior by relying on many variables in describing behavior making the research more complicated respectively. Multivariate Research being used for behavioral sciences research. Which the research in this manner will have the basis of the analysis from regression analysis and experimental research. (Berry, 2018, pp. 1-7) Multivariate research will be analyzed with complex statistical techniques such as multiple regression analysis, discriminant function analysis, multivariate analysis of variance (MANOVA), component and factor analysis, path analysis and Structural Equation Modeling (Meyers et al., 2005) Research design may have a simple style to the complicated research design. Thus, determining the sample size for multivariate behavioral sciences research that utilizes these analytical techniques can be complicated due to the nature of the data and the conditions involved.

Determining the sample size of good behavioral science research must take into the type of research consideration, for example: The study for independent results (Independent Outcomes) will be considered in terms of providing accurate analysis results (Precision Analysis), Power Analysis, as well as other conditions that the researcher must be attention to. While other types of research such as Clustered Outcomes, Repeated Measurement Outcomes, Correlated Outcome, Correlated Outcomes from Two-Level Randomized Clinical Trials or Three-Level Randomized Clinical Trials which will be conditional on statistical analysis model and research designs involved in many other factors. (Ahn et al., 2015) such as Cluster-Randomized Trials, Multi-Regional Trials and other. (Kieser, 2020, pp. 167-181) The most important fundamental principle of behavioral science research is that the larger the sample size have the better probability of the sample being representative than the smaller sample size. (Privitera, 2016, pp. 273 - 275) (Gravetter, 2018, p. 113)

In this article to focus on the Structural Equation Modeling (SEM). Which is an option that is more popular for statistical analysis of behavioral sciences research. In the quantitative research paradigm. Because it is the way to help researchers create models showing complex relationships of human behavior and while having to consider the error in measuring latent variables that occur during study. (Kline, 2015) Suitable for the complex behavioral research of research issues such as multivariate behavioral sciences research. The research problem arises in the process of determining the appropriate sample size for analysis. There are suggestion and methods for determining sample size that are complicated and relying on the estimation of many parameters in consideration.

The method of determining the sample size is often considered in terms of the number of observed variables for normal distribution data. Bentler and Chou (1987) suggestion a low ratio of 5 cases per variable is recommended when the latent variable has multiple identifiers. The thumb rule, or ten-finger rule, presents that structural equation model analysis. The acceptable sample size is 10 cases per indicator variable used where the number of samples is sufficient for the lowest possible threshold for analysis. Most researchers agree that structural equation model need a large sample size for analysis. Many researchers use the minimum threshold of 300 or more. (Comrey & Lee, 2013; Tabachnick & Fidell, 2012) But this conclusion may not be suitable for most analysts. Because there is no internationally accepted correct calculation or method. For determining the sample size for the analysis of structural equation models some researchers and statistical scholars recommend using the observed-to-approximate parameter (N: Q) ratio as a guide. (Kline, 2015) It is recommended that the N:Q ratio be 20: 1 for each approximate parameter in the model (participants: parameter). Some experts suggest that the N : Q ratio can be as low as 10 : 1 (Schreiber et al., 2006) or 5 to 1 can still be done. (Bentler & Chou, 1987) Obviously, there is a lot of variance and uncertainty in determining sample sizes for structural equation model analysis. Although this is the approach proposed by academics specializing in structural equation model analysis.

Determination of sample size for the Structural Equation Modeling analysis also depends on the number of observed variables (indicator) per latent variables. (Marsh et al., 1998; Marsh & Hau, 1999) Some researchers propose that observed indicators that have greater numbers per factor may be compensated with small samples and the larger sample size may compensate some indicators to the factors as well. Consider that the sample size of n = 50 is sufficient for the confirmatory factor analysis (CFA) model with 6-12 indicator variables per factor. While some researchers offer that sample size should be at least n = 100 cases for analyzing models with 3-4 indicators per factor (variable). (Boomsma 1985; Marsh & Hau, 1999) However if only 2 indicators per factor in the component factor analysis model the sample size required for analysis must be at least not less than 400 cases.

Structural Equation Modeling analysis the same sample size is used for factor analysis. This is an analytical technique that uses large samples. (Tabachnic & Fidell, 2007 cited in Velicer & Fava, 1998; Hair et al., 2019; Härdle & Simar, 2019) Therefore, such an analysis cannot be used the sample size determination as a typical general survey research. However, due to new statistical testing techniques that has been developed in the later era. The Structural Equation Modeling analysis is acceptable when there are at least 60 samples or more. (Bentler & Yuan, 1999) There are two popular assumptions made in the case of possible sample sizes they should be at least 50 or over 200 or more than eight times the number of variables used in the analytical model. (Thakkar, 2020) There is also an suggestion of Hair et al. (2014, pp. 572-573) The researchers need to consider sample size conditions for Structural Equation Modeling analysis many things.

Each of these considerations is discussed in the following (1) Multivariate Normality. As data deviate more from the assumption of multivariate normality, then the ratio of respondents to parameters needs to increase. (2) Estimation Technique. The most common SEM estimation procedure is maximum likelihood estimation (MLE). Simulation studies suggest that under ideal conditions, MLE provides valid and stable results with sample sizes as small as 50. As one moves away from conditions with very strong measurement and no missing data, minimum sample sizes to ensure stable MLE solutions increase when confronted with sampling error. (3) Model Complexity. Simpler models can be tested with smaller samples. In the simplest sense, more measured or indicator variables require larger samples. However, models can be complex in other ways that all require larger sample sizes. (4) Missing Data. Missing data complicate the testing of SEM models and the use of SEM in general because in most approaches to remedying missing data, the sample size is reduced to some extent from the original number of cases. (5) Average Error Variance of Indicators. Recent research indicates the concept of communality is a more relevant way to approach the sample size issue. Communalities represent the average amount of variation among the measured/indicator variables explained by the measurement model.

As SEM matures and additional research is undertaken on key research design issues, previous guidelines such as "always maximize your sample size" and "sample sizes of 300 are required" are not appropriate. Larger samples generally produce more stable solutions, particularly when data or measurement problems exist. (Hair et al., 2019, p. 633) Based on the discussion of sample size, the following suggestions for minimum sample sizes are offered based on the model complexity and basic measurement model characteristics:

1. Minimum sample size-100: Models containing five or fewer constructs, each with more than three items (observed variables), and with high item communalities (.6 or higher).

2. Minimum sample size-150: Models with seven constructs or less, at least modest communalities (.5), and no underidentified constructs.

3. Minimum sample size-300: Models with seven or fewer constructs, lower communalities (below .45), and/or multiple underidentified (fewer than three) constructs.

4. Minimum sample size-500: Models with large numbers of constructs, some with lower communalities, and/or having fewer than three measured items.

In addition to these characteristics of the model being estimated, sample size should be increased in the following circumstances: (1) data deviates substantially from multivariate normality, (2) sample-intensive estimation techniques (e.g., ADF) are used, or (3) missing data exceeds 10 percent. Also, remember that group analysis requires that each group meet the sample size requirements just discussed. Finally, the researcher must remember that the sample size issue goes beyond being able to estimate a statistical model. The sample size, just as with any other statistical inference, must be adequate to represent the population of interest, which should be the overriding concern of the researcher. At the risk of being repetitive, inference to the population is the most important consideration in determining sample size. In addition to the more general research design issues discussed in the prior section, SEM analysis has several unique issues as well. These issues relate to the model structure, estimation technique used, and computer program selected for the analysis. (Hair et al., 2019, p. 633)

Tabachnick and Fidell (2012) The researcher must consider various conditions when determining the sample size for factor analysis of proposed. Thoroughly assembling the determination of the sample size of the analysis with the suggestion of Comrey and Lee proposed in 1992. (Tabachnick & Fidell, 2007) indicated give as a guide sample sizes of 50 as very poor, 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 as excellent. As a general rule of thumb, it is comforting to have at least 300 cases for factor analysis. Solutions that have several high loading marker variables (> .80) do not require such large sample sizes (about 150 cases should be sufficient) as solutions with lower loadings and/or fewer marker variables. However, the offer of MacCallum et al. (1999 cited in Tabachnick & Fidell, 2014) show that samples in the range of 100 - 200 are acceptable with well determined factors (i.e., most factors are defined by many indicators, such as marker variables with loadings of 0.80 or higher) and high item communalities (squared multiple correlations among variables) in the range of .45 - .55. At least 300 cases are needed with low item communalities, a small number of factors, and just three or four indicators for each factor. Sample sizes well over 500 are required under the worst conditions of low item communalities and a larger number of weakly determined factors.

Additionally, Denis (2021) proposes that sample sizes of 300 and above are the minimum requirements for compositional analysis. But if the value very low communalities and Factors are poorly determined requires a sample size of 500 or more.

Principles of sample size considerations for factor analysis Wolf et al. (2013) proposed that there are 4 major considerations such as (1) Effect of number of factors. Within the CFAs, increasing the number of latent variables in a model resulted in a significant increase in the minimum sample size when moving from one to two factors, but this effect plateaued, as the transition from two to three factors was not associated with a concomitant increase in the sample size. (2) Effect of number of indicators. Overall, models with fewer indicators required a larger sample relative to models with more indicators. A one-factor, four-indicator model with loadings of .50, .65, and .80 required sample sizes of 190, 90, and 60, respectively, while a one-factor, six-indicator model required sample sizes of 90, 60, and 40, respectively (3) Effect of magnitude of factor loadings. Models with stronger factor loadings required dramatically smaller samples relative to models with weaker factor loadings. (4) Effect of magnitude of factor correlations. As described in the notes to also evaluated the effect of increasing the factor intercorrelation from .30 to .50. On average, the increased factor relationship was associated with 78 fewer participants in the minimum acceptable sample size for the CFA models with .50 factor loadings, 55 fewer participants for CFA models with .65 factor loadings, and 37 fewer participants for CFA models with .80 factor loadings.

Principles of sample size considerations for structural equation modeling Wolf et al. (2013) proposed that there are 4 major considerations such as (1) Effect of magnitude of regressive paths. Mediation models with larger effects tended to achieve adequate statistical power for the direct and indirect effects in the model with smaller sample sizes. (2) Effect of Missing Data. Greater amounts of missing data in the two-factor CFA and mediation models generally necessitated larger sample sizes. (3) Effect of Latent Variables. The comparison of latent versus observed variables in the mediation model demonstrated that no amount of increasing the sample size of single indicator models could account for bias in those results; the attenuation in the magnitude of the parameter estimates was directly related to the degree of unspecified unreliability in the measure. (4) Stability of Results. With a few exceptions, solutions that met all a priori criteria at a given sample size were stable relative to the results of the analysis at the next largest sample size. Wolf et al. (2013) observed somewhat greater instability of results, however, with respect to the reanalysis of the best solutions using a new seed number. Specifically, in 34% of the analyses, the minimum sample size increased (average increase in sample size = 24 cases, range = 10–50); in 16% of the analyses, the minimum sample size decreased (average decrease in sample size = 18 cases, range = 10–30) and in 50% of the analyses, the minimum necessary sample size was equal across analyses using the two seed numbers.

Soper (2023) has created a program for calculating the appropriate sample size for the Structural Equation Modeling analysis. The appropriate sample size will be under 5 conditions: (1) Expected effect size is the minimum absolute anticipated effect size for the Structural Equation Modeling by convention values of 0.1, 0.3 and 0.5 are considered small, medium and large, respectively (2) Latent variables is the number of unobserved (latent) variables in the Structural Equation Modeling (3) Observed variables is the number of indicator (observed) variables in the Structural Equation Modeling (4) p-value is the probability of the study. This value should typically be less than or equal to .05 and (5) Statistical power is the desired statistical power level (should typically be greater than or equal to 0.80).

In the opinion of the author, the researchers should set the value of the test. Because an issue related to statistical power. Power, first and foremost, is a probability. Power is the probability of rejecting a null hypothesis given that the null hypothesis is false. It is equal to 1 – β (i.e., 1 minus the type II error rate). If the null hypothesis were true, then regardless of how much power one has, one would still not be able to reject the null. (Intensive literature review will help reduce the chances of the null hypothesis will be false assumptions) Although we accept null hypothesis it does not cause any damage. Statistical power we may think of it somewhat in terms of the sensitivity of a statistical test for detecting the falsity of the null hypothesis. If the test is not very sensitive to departures from the null (i.e., in terms of a particular alternative hypothesis), we will not detect such departures. If the test is very sensitive to such departures, then we will correctly detect these departures and be able to infer the statistical alternative hypothesis in question. (Denis, 2021, p. 67)

Research that uses this method of determining research sample size includes: psychometric evaluation of the brief acculturation scale for hispanics by Mills et al. (2014), Application of the stimuli-organism-response (SOR) framework to online shopping behavior by Peng and Kim (2014), A missing link in understanding revisit intention - The role of motivation and image by Li et al. (2010), Understanding the intention to use technology by preservice teachers: An empirical test of competing theoretical models by Teo and Van Schaik (2012).

Chomeya et al. (2022) Suggestions for an RSS sample size table for structural equation modeling (SEM) in multivariate behavioral sciences research could include:

Table 1

RSS sample size table for Structural Equation Modeling : SEM

N	n	N	n	N	n	N	n	Value	n
60	52	700	248	4,000	351	40,000	381	**For large sample size analysis technique**	
70	59	800	260	5,000	357	50,000	381		
80	66	900	269	6,000	361	60,000	382	Very poor	50
90	73	1,000	278	7,000	364	75,000	382	Poor	100
100	80	1,100	285	8,000	367	80,000	382	Fair	200
200	132	1,200	291	9,000	368	90,000	383	Good	300
300	169	1,400	302	10,000	370	100,000	383	Very good	500
400	196	1,500	306	15,000	375	200,000	383	Excellent	1,000
500	217	2,000	322	20,000	377	300,000	383	Exceptional	1,200
600	234	3,000	341	30,000	379	400,000	383	Profound	1,500

However, the sample size for the analysis of structural equation modeling is complicated and still do not have the most exact standard for determining the appropriate sample size for analysis. The rules that are defined are not available in all situations of the analysis of structural equation modeling. (Muthén & Muthén, 2002) The researcher analyzed the structural equation modeling may be considered from many. Factors consisting of the appropriate sample size for the most complete and reliable analysis results.

Monte Carlo simulation methods are becoming increasingly popular for in-depth discussions in structural equation modeling analysis. (Wolf et al., 2013) Which this method is expected to be more popular in the future. (Barbu & Zhu, 2020; Mitchell, 2017; Rubinstein & Kroese, 2016) However, a factor that influences another important sample size that researchers must consider is ethics of research. Especially if the sample size is too large, the sample may be used to participate in unnecessary research. Which may be an ethical issue of research. On the other hand, if the sample is too small it is unlikely to make research successful. Researchers must consider the significance level. And statistical principles used in the analysis in order for the results to be in the scope of the expected results in the statistical. (Gravetter, 2018)

Conclusion

Determining the sample size for Structural Equation Modeling analysis in multivariate behavioral sciences research can be approached in various ways, taking into account both the nature of the data and the research design. Researchers must consider factors such as the specific research aims, the expected effect size or minimum effect size, and the number of latent variables under study. The number of observed variables that can be validity measured, error or significant levels that can be accepted, power of statistical testing as well as considering the budget of research and in terms of research in other ways many conditions. Ultimately the researchers will use any principle in determining sample size of Structural Equation Modeling analyze for multivariate behavioral sciences research must consider in 2 conditions (1) to estimate the parameters of various types of analysis techniques and (2) to the truly representativeness with the sample size that is sufficient for the generalization to population (minimum requirement) studies.

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