A REVIEW OF STRUCTURAL EQUATION MODELING SAMPLE SIZE IN SUPPLY CHAIN MANAGEMENT DISCIPLINE

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Abstract:

Determining sample size requirements for structural equation modeling (SEM) is a challenge often faced by investigators, peer reviewers, and grant writers. One study found that 80 per cent of the research articles in a particular stream of SEM literature drew conclusions from insufficient samples. This paper aims to suggest substantive applications of techniques verifying adequate sample size needed to produce trustworthy result when researchers conduct structural equation modeling technique in supply chain management (SCM) discipline. The paper reviewed a set of 42 empirical research articles in supply chain management research with respect to the application of structural equation modeling, choice of its sample size, conducted modern techniques and related factors affecting the decision. It is concluded that most of the studies achieve widely accepted rules of thumb with sufficient observations in sample size. However, there is no considerable attention paid to important influenced factors and very few studies take notice of modern sample size estimation technique such as statistical power analysis. Based on the critical analysis, recommendations are offered.

Keywords: *sample size, structural equation modeling, supply chain management*

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1. Introduction

Supply Chain Management is a topic of interest and importance among researchers and logistics managers since it is considered source of competitive advantages (Mangan, Lalwani, Butcher, & Javadpour, 2012). SCM theoretically focus on the management, across a network of organizations, of both relationship and flows of materials and resources with the purposes to create value, enhance efficiency, and satisfy customers (Coyle, Langley, Novack, & Gibson, 2013). Mangan et al. (2012) also said that it is not enough to improve efficiencies within an organization, but the whole supply chain has to perform effectively and efficiently. Since SCM cut across several areas such as logistics, operations management, marketing, purchasing, and strategic management, to

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name few, SCM research shows a high degree of multidisciplinary and a broad scope of approaches incorporating of qualitative and quantitative research methods (Marcus & Jurgen, 2005).

Despite the fact that quantitative approach dominates research in logistics and supply chain phenomena (Susan, Donna, & Teresa, 2005), research still lack a focus on methodology and theory development (Marcus & Jurgen, 2005). Research will undoubtedly advance through rigorous empirical approaches within theory construction. In the SCM discipline, descriptive statistics form a major part in empirical-quantitative research, while more advanced techniques like Structural Equation Modeling (SEM), Path Analysis, Multivariate Analysis of Variance (MANOVA) and Cluster Analysis are not used very often, less than 6 per cent in total (Gunjan & Rambabu, 2012). Descriptive statistics are important but for constructing a theory, inferential statistics is even more essential. It is thus imperative for SCM researchers to adopt higher forms of techniques, along with descriptive statistics. SEM is one of well-proven techniques in fields of economics and management research, as it allows for validity of the structures and constructs in proposed theoretical models to be tested (Marcus & Jurgen, 2005).

SEM is a collection of statistical techniques that has been used to test and estimate causal relations by providing a framework for analysis that includes several traditional multivariate procedures, for example factor analysis, regression analysis, and discriminant analysis (Barbara & Linda, 2001). Structural equation models are often visualized by a graphical path diagram and the statistical model is usually represented in a set of matrix equations. SEM is relevant to both theory testing and theory development since it allows both confirmatory and exploratory modeling. However, SEM is a largely confirmatory, rather than exploratory technique (Herbert, Alexandre, Philip, & Gurvinder, 2014). That is, researchers are more likely to use SEM to determine whether a certain model is valid, rather than using SEM to discover a suitable model.

The fact that SEM can combines measurement models - confirmatory factor analysis and structural models - regression analysis into a simultaneous statistical test, enabling complex interrelated dependence relationships to be assessed, makes it especially valuable to researchers in SCM (Joseph, William, Barry, & Rolph, 2010). Barbara and Linda (2001) claimed that SEM is the analysis technique that allows complete and simultaneous test of all the relationships that are complex and multidimensional. Although SEM is being used in SCM quantitative research, SEM approach was not used frequently (only 3.34 per cent) comparing with other data analysis techniques (Gunjan & Rambabu, 2012). Many researchers are reluctant from SEM because of the fact that it requires large sample size. Besides, there is no clear guidance on determination of optimal sample size.

The primary objectives of this paper are: 1) to provide an overview of basic statistical issues related to sample size determination in SEM approach, 2) to discuss findings in the literature relevant to influenced factors and methods, and 3) to discuss substantive applications of techniques verifying adequate sample sizes needed to obtain reliable outcome in SCM research. The paper starts with the review of sample size issues in general empirical research. The second section is devoted to the discussion of the analysis of sample size decision together with related factors and methods in research studies in SCM discipline. In section 3, guideline for future research will be recommended. Finally, the paper is concluded in section 4.

2. Sample size issues in Structural Equation Modeling

One of the most critiques that has been raised against the use of SEM is sample size determination (Lei & Wu, 2007). Sample size determination is the act of choosing adequate number of observations to include in a statistical sample. One study found that 80 per cent of the research articles in a particular stream of SEM literature utilized insufficient samples (Christopher, 2010). SEM is considered a large-sample technique and more sensitive to sample size than other multivariate approaches (Kline, 2005). Given the fact that sample size provides a basis for the estimation and testing result, the issue of sample size is a serious concern.

As in any statistical modeling, determination of appropriate sample size is crucial to SEM. It is widely recognized that small sample size could cause a series of problems including, but not limited to, failure of estimation convergence, lowered accuracy of parameter estimates, small statistical power, and inappropriate model fit statistics (Jichuan & Xiaoqian, 2012) which might lead to misleading results and improper solutions. In SCM discipline, SEM is mainly based on covariances, which are less stable when estimated from small samples (Cristina, Rudolf, & Eva, 2005). Therefore, sufficient sample required for a particular study should be determined to get an accurate snapshot of the phenomena examined.

Although determination of appropriate sample size is a critical issue in SEM application, there is no consensus in the literature regarding what would be the appropriate sample size for SEM. There are several studies seeking answer to the question of how many observations necessary to have a good SEM model. This section will review the applied pattern in the literature regarding what would be the proper sample size for SEM. The rules of thumb for sample size needed for SEM will be firstly reviewed, and then different approaches to estimate an adequate sample size for a SEM model will be discussed.

2.1. Rules of thumb

Over the years, general rules of thumb for determining sample size in SEM include establishing a minimum, having a certain number of observations per variables, having a certain number of observations per parameters estimated (Rachna & Susan, 2006)2006.

In the first two approaches, there is no recommendation for the sample size that is broadly relevant in all contexts (Andrew & Niels, 2005). Sample of 100 is usually considered the minimum sample size for conducting SEM. Some researchers consider an even larger sample size for SEM, for example, 200 (Jichuan & Xiaoqian, 2012). Sample size is also considered in light of the number of observed variables. For normally distributed data, a ratio of 5 cases per variable is sufficient when latent variables have multiple indicators. However, a accepted rule of thumb, in general, is 10 cases per indicator variable in setting a lower bound of an adequate sample size (Jichuan & Xiaoqian, 2012).

The ratio of observations to number of free estimated parameters has also been given attention to determine the sample size. A higher ratio is preferred. Jichuan and Xiaoqian (2012) claimed that the minimum sample size should be at least 10 times the number of free parameters with strongly kurtotic data. Kline (2010) gave relative guidelines based on the ratio of cases to estimated parameters and advised that a 20:1 cases to parameter ratio could be regarded as desirable, 10:1 as realistic, and 5:1 as doubtful.

One of the strengths of SEM is its flexibility, which permits examination of complex associations, use of various types of data and comparisons across alternative models. However, these features of SEM also make it difficult to develop generalized guidelines or rules of thumb regarding sample size requirements (Erika, Kelly, Shaunna, & Mark, 2013). Such rules are problematic to a certain degree since there are no rules of thumb that apply to all situation in SEM and may lead to over or under-estimated sample size requirements (Jichuan & Xiaoqian, 2012).

2.2. Set of influenced factors

Determination of sample size needed for SEM is complicated. There is no absolute Determination of sample size needed for SEM is complicated. There is no absolute standard in regard to an adequate sample size. In addition to the number of free parameters need to be estimated and the number of indicators per latent variables, sample size needed for SEM is also dependent on many other factors that are related to data characteristics and the model being tested. Four considerations affecting the required sample size for SEM include the following: multivariate normality of the data (Joseph et al., 2010; Tenko & Keith, 1995), estimation technique (Cristina et al., 2005; Joseph et al., 2010; Lei & Wu, 2007; Tenko & Keith, 1995), model complexity (Cristina et al., 2005; Joseph et al., 2010; Lei & Wu, 2007; Tenko & Keith, 1995), the amount of missing data (Joseph et al., 2010).

Multivariate Normality - As data diverges from the assumption of the multivariate normality, then the ratio of observations to parameters needs to increase. A generally suggested ratio to minimize problems with divergence from multivariate normality is 15 observations for each free parameters estimated in the model (Joseph et al., 2010).

Estimation Technique – The most popular SEM estimation method is maximum likelihood estimation (MLE). Studies suggest that under ideal conditions (multi-normal data from a large sample), MLE provides valid and stable results with sample sizes as small as 50 (Tenko & Keith, 1995). Samples sizes should increase as conditions are moved away from a very strong measurement and no missing data to sampling errors. Given less ideal conditions, Joseph et al. (2010) recommend a sample size of 200 to provide a sound basis for estimation.

Model complexity – In a simple sense, more observed variables would require larger samples. However, models can become complex in other ways, which include constructs requiring more parameters, constructs having small number of measured variables and research implementing multi-group analysis. All of those model complexity factors lead to the need for larger samples (Lei & Wu, 2007).

Missing data – This issue complicates the use of SEM in general because in most methods to solving missing data, the sample size is reduced to some extent from the original number of cases. Failure to account for missing data when determining sample size requirements may ultimately lead to insufficient sample size. Hence in order to compensate for any problems that missing data causes the researcher should plan for an increase in sample size (Joseph et al., 2010).

Average error variance of indicator, which is also referred to *communality*, is a more relevant way to approach the sample size issue. Communalities represent the average amount of variation among the measured variables explained by the measurement model. Studies show that larger sample sizes are required as communalities become smaller (Joseph et al., 2010).

2.3. Power Analysis

Adequacy of sample size has a significant impact on the model fit. Most of the evaluation criteria for assessing overall goodness of fit of an SEM are based on the Chi-square statistics. However, this test statistic has been found to be extremely sensitive to sample size (Thomas, 2001). For large samples it may be very difficult to find a model that cannot be rejected due to the direct influence of sample size, even if the model actually describes the data very well. Conversely, with a very small sample, the model will always be accepted, even if it fits rather badly (Hox & Bechger, 2007). Given the sensitivity of the chi-square statistic for sample size, researchers have proposed a variety of alternative approaches. One of the most popular modern technique to estimate sample size for specific SEM models are through conducting power analysis (Jichuan & Xiaoqian, 2012).

Some model-based approaches have been increasingly used to conduct power analysis and estimate sample size for specific SEM models. In these approaches either statistical power is estimated given a sample size and significance level (e.g., 0.05) or sample size needed to reach a certain power (e.g., 0.80) is estimated (Lei & Wu, 2007). Power analysis can either be done before (a priori or prospective power analysis) or after (post hoc or retrospective power analysis) data are collected. A priori power analysis is conducted prior to the research study, and is typically used in estimating sufficient sample sizes to achieve adequate power.

Recently, sample size needs to be determined preferably based on a priori power consideration. There are different modern approaches to power estimation in SEM such as Satorra and Saris's method , Monte Carlo simulation, and the root mean square error of approximation (RMSEA) method as well as methods based on model fit indices including MacCallum, Browne, and Sugawara's method and Kim's method. However, an extended discussion of each is beyond the scope of this section.

3. Research Methodology

The comprehensive plan for the review of structural equation modeling sample size in supply chain management discipline is presented in three parts: article selection, journal classification, and analysis of articles.

The collected articles were taken from four major management science publishers namely, Science Direct, ProQuest, Emerald Online and EBSCOhost. These publications were considered for article collection because the majority of journals publishing SCM research are in these publications. In each publication, exact terms such as "supply chain", "supply chain management", or "SCM", and "structural equation modeling" or "SEM" were searched in article keywords. Through this process, more than 90 studies were identified for possible consideration. However, after a full text review, only 42 research studies, published from 2003 to 2013, were found suitable for the purpose of this study, as they were the only SCM-related studies with SEM technique. Our collection of studies included those using the full SEM framework as well as those using special cases of SEM, such as path analysis, confirmatory and exploratory factor analysis.

42 research studies belong to 15 different journals which are classified into two groups: *Accounting, Organization and Society; Decision Support System; Information and Management; and Journal of Operation Management (Group A)*; *Journal of Purchasing & Supply Management; Industrial Marketing Management; International Journal of Operation & Production Management; International Journal of Production Economics; The International Journal of Management Science; Benchmarking an International Journal; Expert System with Application; Internal Business Review; International Journal of Physical Distribution and Logistics Management; International Journal of Production Research; The International Journal of Logistics Management (Group B)*. The classifications of these journals are based on the revised edition of 'Excellence in Research for Australia' (ERA) journal and conference ranking list conforming to the international standards conducted by Australian Research Council (ARC) (UQBS, 2012). In the ERA ranking list, the journals are ranked using four tiers of quality ranking: A* (top 5%): "virtually all papers they publish will be of a very high quality"; A (next 15%): "the majority of papers in a Tier A journal will be of very high quality"; B (next 30%): "generally, in a Tier B journal, one would expect only a few papers of very high quality"; C (next 50%): "journals that do not meet the criteria of higher tiers". In this research, the A* and A ranked journals will be put into group A. The B and C ranked journals in ERA list will be then classified into group B of the research. The primary aim of this journal group classification is to compare and identify the most advanced sample size estimation techniques, which have been used in those articles published in leading journals.

The analysis of all the reviewed articles is descriptive in nature. This research will be engaged in trend and pattern analysis so as to develop better understanding of the use of SEM sample size estimation methods in SCM discipline. It also aims to suggest specific avenues for improvement. The results will be presented using tables.

4. Critical analysis of current practices

The analysis of 42 articles which are categorized into 2 groups A and B examines rules of thumb based on the ratio of observation per indicator variable or free parameters in the proposed SEM models. Power analysis techniques and set of relevant influenced factors such as multivariate normality, SEM estimation technique and missing data are also examined.

Table 1. Eight categories of Cleantech

No	Code	Sample Size	Para-meter	Cons-truct	Indicator Variable	Observation/ Per Indicator variable	Observation/ Per Free Parameter	Multivariate Normality	Estimation Technique	Missing data	Commu-nality	Power Analysis
Analysis of articles in group A												
1	1a	77	7	5	48	1.6	11.0	Mentioned	Using PLS		Mentioned	
2	1b	310	6	7	37	8.4	51.7		Using PLS		Mentioned	
3	1c	134	5	5	15	8.9	26.8		MLE	2.2%		
4	1d	473	9	6	38	12.4	52.6				Mentioned	Applied
5	1e	111	4	4	12	9.3	27.8		MLE	13.28% with plan		
6	1f	116	10	10	26	4.5	11.6		Using PLS		Mentioned	
7	1g	196	21	10	47	4.2	9.3	Mentioned				
8	1h	370 255	13 13	8 8	28	13.2 9.1	28.5 19.6		Multi-group analysis	9.1% 12%	Mentioned	
9	1i	398	11	6	23	17.3	36.2		MLE			
10	1j	221	14	6	20	11.1	15.8	Mentioned	MLE	4.7%		Applied
11	1k	117	20	8	35	3.3	5.9		MLE	7.1%		Applied
12	1l	241	8	6	18	13.4	30.1					
13	1m	221	7	6	21	10.5	31.6	Mentioned	MLE	8.3%		
14	1o	211	6	3	16	13.2	35.2		Other	12.6% with plan		
15	1p	176	17	3	14	12.6	10.4	Mentioned			Mentioned	
16	1q	115	12	10	55	2.1	9.6			5%		Applied
17	1r	57	4	4	14	4.1	14.3		MLE			
18	1s	218	12	6	12	18.2	18.2	Mentioned	Using PLS	3.5%		
19	1t	131	6	5	13	10.1	21.8	Mentioned		7.1%		

20	1u	142	6	4	18	7.9	23.7		Other		Mentioned	
21	1v	418	3	3	21	19.9	139.2	Mentioned		2.4%	Mentioned	
Analysis of articles in group B												
22	2a	476	7	5	11	43.3	48		MLE	10% with plan		
23	2b	117	4	4	22	5.3	29.3		MLE			
24	2c	243	6	5	22	11	40.5					
25	2d	103	4	4	15	6.9	25.8					
26	2e	101	5	4	12	8.4	20.2					
27	2f	196	3	3	12	16.3	65.3					
28	3a	151	10	10	46	3.3	15.1					
29	3b	711	10	6	25	28.4	71.1	Mentioned				
30	3c	205	4	6	23	8.9	51.3		Using PLS			
31	3e	285	9	6	35	8.1	31.7		Other			
32	3f	52	9	6	26	2.0	5.8		Other			
33	3h	103	9	4	26	4.0	11.4					
34	3i	65	6	4	24	2.7	10.8		MLE			
35	3j	262	4	4	18	14.6	65.5			1.5%		
36	3k	234	13	6	35	6.7	18.0		MLE	6%		
37	3l	625	6	4	18	34.7	104.2	Mentioned	MLE			
38	3m	325	9	6	21	15.5	36.1					
39	3n	42	14	4	18	2.3	3.0					
40	3p	358	24	4	21	17.0	14.9					
41	3q	371	22	6	16	23.2	16.9					
42	3r	180	10	6	18	10.0	18.0					

Source: Author's own compilation

The following table demonstrates the result of the analysis of 42 SCM-related empirical studies categorized in two journal group A and B. Since there is a lack of consensus on determining the minimum sample size and rules of thumb for conducting SEM, sub-criteria are brought up. Apart from rules of thumbs, other criteria including consideration of multivariate normality, SEM estimation technique, missing data and the application of power analysis techniques are also evaluated.

Table 2: Result of the analysis of 42 empirical studies applying SEM in the discipline of SCM

Criteria Number (N=21)	Ranking A Journals		Ranking B & C Journals	
	Percentage (N=21)	**Number (N=21)**	**Number (N=21)**	**Percentage (N=21)**
Average sample size	214		248	
Minimum Sample Size				
100 observation	20	95%	18	86%
150 observation	13	62%	14	67%
200 observation	11	52%	12	57%
Observation per indicator variable				
Ratio 10:1	11	52%	10	48%
Ratio 5:1 (less than ratio 10:1)	5	24%	6	29%
Average number of parameters	9.7		9	
Average ratio of sample size to number of parameters estimated	22		27.6	
Observation per free parameter				
Desirable ratio 20:1	11	52%	11	52%
Realistic ratio10:1 (less than ratio 20:1)	7	33%	7	33%
Doubtful ratio 5:1 (less than ratio 10:1)	3	14%	1	5%
Multivariate Normality consideration	8	38%	2	10%
Estimation Technique				
MLE	7	33%	5	24%
Using PLS	4	19%	1	5%
Missing data				
Missing data	11	52%	3	14%
Missing data with plan	2	10%	1	5%
Communality	8	38%	0	0%
Power Analysis application	4	19%	0	0%

Source: Author's own compilation

There are no large differences between articles in journal group A and B in terms of sample size average, minimum sample size and ratio of observation per indicator variable. The average sample size of journal articles in group A and B are 214 and 248, which are considered large enough since some articles explicitly present the intention to collect data as many as possible (Gensheng & George, 2011; Keah, Vijay, Chin-Chun, & Keong, 2010; Paul, Oahn, & Kihyun, 2010; Peter, Kevin, Marcos, & Marcelo, 2010; Prakash & Damien, 2009; Shaohan, Minjoon, & Zhilin, 2010; Su & Chyan, 2010; Zach, Nancy, & Robert, 2011). Most of the studies in both group achieve the lower bound of 100 observations in sample size, with 95 per cent in group A and 86 per cent in group B. A reasonable required sample size, N = 150 (Kline, 2010), is attained by around two thirds of reviewed articles in group A (62 per cent) and in group B (67 per cent). It can also be easily seen from the table 2 that the ratio of observation per indicator variable of 10:1 is attained by roughly half of empirical works in both journal group A and B, 52 per cent and 48 per cent respectively. These figures indicate that, on average, SEM sample sizes considered in previous studies in SCM discipline are broadly satisfactory for achieving widely accepted rules of thumb with regard to minimum required sample size and ratio of observation per indicator variable.

Table 2 shows that, overall, the average numbers of parameters estimated in the papers examined in two groups were about 9.7 and 9. The means sample size were 214 and 248 correspondingly, resulting in averages ratio of sample size to number of free parameters of about 22:1 for papers in group A and 27.6:1 in group B. More specifically, 52 per cent of models in two groups of journals acquire desirable ratio of observation per free parameter (20:1). 33 per cent of research in each group have realistic ratio of 10:1 while the lower end of the ratio are significant small in both group. These figures show that sample size are often toward the upper end of levels that are considered acceptable to obtain trustworthy parameter estimates and valid test of significance.

However, it can be seen from Table 2 that there is no considerable attention paid to other associated factors when SEM sample size is determined in SCM research discipline. It is clear that there are large differences between studies in two groups. Studies with high quality in group A which are published in leading journals examined more carefully by evaluating sample size requirement with regard to influenced factors including multivariate normality, communality, missing data and estimation technique.

While studies in journal group B take almost no notice of multivariate normality and communality, eight (38 per cent) of reviewed studies in group A discussed about the effect of these factors on sample size decision. For example, in order to ensure the multivariate normality assumption of all the variables satisfied, Michael and Nallan (2009) conducted Kolmogorov-Smirnov test. Mardia measure of multivariate kurtosis was also taken into account in one of A ranking journal research (Ganesh & Sarv, 2008). Antony, Augustine, and Injazz (2008) suggested that before conducting SEM, sample scale need to be evaluated for multivariate normality to guarantee that data could be reliably tested. In the discussion of communality factor to support necessary sample size in SEM, Peter et al. (2010) stated that communality of items should be highly considered. It measures the percentage of variance from one variable that can be explained by all the remaining factors together. The statistics look small but can be significant if the item is important to improve the definition of the supply chain model.

Although more than half of empirical research in ranked A journals refer to missing data during the sample collection process, only 10 per cent develops plan for an increase in sample size including the design of survey, ease of use and the maintenance of respondents' interest to offset any problems with missing data (Mei & Qingyu, 2011; Paul, Robert, Lawson, & Kenneth, 2006). Among the 21 papers studies in group B, the issue of missing data was addressed in three (14 per cent) papers, only one of them extend to a plan to justify appropriate remedy. These results suggest that SCM researchers often neglect to inform readers how missing data are handled in SEM analysis.

One of the factors make SEM model complex, which requires larger sample size is multi-group analysis. A research examining supply chain relationship between buyer and supplier conducted by Gilbert, Judith, and Daniel (2010) in A ranking journals utilizes multi-group approach. In this empirical work, it is clearly defined that since constructs, number of items of construct are the same in each group and the sample sizes exceed the recommended minimum, the analysis using SEM will yield accurate results.

Maximum Likelihood Estimation (MLE) is the dominant approach for estimating SEM (Kline, 2005). 20 studies (48 per cent) in the review did not report the estimation method used. Among the models that reported the estimation method, most of the analysed academic articles (76 per cent) use covariance-based SEM approach including the MLE estimation techniques. MLE requires a relatively larger sample size and under less ideal condition it is recommended to have at least 200 observations. It can be seen from the Table 2 that 52 and 57 per cent of studies in group A and B correspondingly fulfill the requirement of 200 cases. However as the sample sizes are large, the MLE method becomes more sensitive and almost any difference is detected, making goodness-of-fit measures suggest poor fit (Keah et al., 2010; Paul et al., 2010; Prakash & Damien, 2009; Shaohan et al., 2010; Suhong, Subba, Ragu-Nathan, & Bhanu, 2005).

Unlike covariance-based SEM, Partial Least Squares (PLS) is a components-based approach to structural modeling and has lower sample size requirement. It can be seen that studies in higher-ranking journals with small sample size took advantage of PLS. Dutch, Lorraine, Robert, and William (2012) and Daniel, Richard, and Gernot (2012) in their research said PLS is best suited for their relatively complex model, the sample size and sample distribution. Dutch et al. (2012) also proclaimed the fit between their goal to develop a new theoretical model based on hypotheses and the use of PLS in their SCM research.

Statistical power is critical to SEM analysis because it has the ability to detect and reject a poor model. However, statistical power is very sensitive with sample size, especially with very large samples, even trivial levels of model misfit can lead to statistical rejection of a model. Therefore, sample size needs to be determined preferably based on a priori power consideration. Few studies in the review mentioned power. There are four studies (19 per cent) in group A mentioned power and only one estimated power explicitly, while none of the articles in journal group B applied statistical power analysis. For example, Canan, Carol, and Robert (2007) addressed the concern about the small sample size by ensuring statistical power satisfied with the significance level 0.05 and sample size reaching a power of 0.80.

5. Guidelines for future research

Determination of required sample size for SEM in multi-disciplinary field such as SCM is complicated. There is no specific standard with regard to an adequate sample size and no rule of thumb that applies to all situations in SEM (Jichuan & Xiaoqian, 2012). Based on the above critical analysis of sample size decision in reviewed SCM studies, the following suggestions, which are adapted from recent studies' recommendations, are offered.

Firstly, in order to calculate the required minimum sample size, it is recommended that researchers will initially conduct SEM priori power analysis before choosing to analyze their data with SEM (Erika et al., 2013; Guy, Vincenzo, & Peter, 2010; Jeffrey & Gregory, 2007; Jichuan & Xiaoqian, 2012; Rachna & Susan, 2006). This power analysis approach has been studied extensively recently. All these studies suggested that when contemplating sample size, investigators prioritize achieving adequate statistical power to observe true relationships in the data. Some model-based approaches, such as Satorra and Saris's method and Monte Carlo simulation, as well as methods based on model fit indices including MacCallum, Browne, and Sugawara's method and Kim's, have been increasingly used to conduct power analysis and estimate sample size for specific SEM models. They can provide statistical power estimates, as well as precision information, for all free parameters involved in a model given a sample size.

Secondly, utilizing PLS approach instead of covariance-based SEM approaches was suggested by Carl and Jürgen (2005) as a basis for theory development within Logistics and SCM research. PLS is a very useful and powerful approach to data analysis especially when the study focuses on exploration rather than confirmation. In addition, PLS has no prerequisites regarding the data distribution and only requires small sample sizes. Sample size should, however, at least exceed ten times the larger value of the block with the largest number of the dependent latent variable (Natasha & Shenyang, 2011).

Thirdly, there are many factors that need to be considered such as model complexity, multivariate normality, communality and SEM estimation techniques, which make rules of thumb more specific. For situations in which large samples of subjects are impractical, less than 100 subjects, researchers should use an analysis method other than SEM. For models requiring multiple-group analysis (Natasha & Shenyang, 2011) or containing less than five constructs, each with more than three items and with high communalities, the minimum sample size should be more than 100. Minimum sample size of 300, lastly, is required for models with seven or more constructs, each with more than three observed variables and with low communities (Joseph et al., 2010). In addition to the number of constructs, observed variables, and item communalities, sample size for SEM should also increase in the situation when data diverges from multivariate normality, or when MLE estimation technique is used, or sample missing exceeds 10 per cent (Joseph et al., 2010).

5. Conclusion

Nearly two decades ago, Tenko and Keith (1995) asserted that there was a lack of generally sound rules of thumb for determination of sample size for SEM. Given the discussed important factors and estimation techniques that influence decision concerning sample size in recent studies, evidence exists that popular approaches have been obtained. Those approaches include establishing a minimum, having a certain number of observations per parameters estimated, and through conducting power analysis. However determination of required sample size is still a complicated issue. Difficulties arise in SEM practice especially in multi-disciplinary field such as SCM that when researchers attempt to determine whether the sample is large enough to yield trustworthy results, yet not so large as to statistically reject reasonable models. Taking into account the consideration that sample size decision is one of the most critical obstacles to the application of SEM in SCM research, it is crucial to have further studies on this issue to provide better guidance on determination of optimal sample size.❑

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Appendix A - List of analysed empirical studies in journal group A

Article Code	Article
1a	(Dutch et al., 2012)
1b	(Peter et al., 2010)
1c	(Ming-Chih, Wen, & Hsin-Chieh, 2010)
1d	(Zach et al., 2011)
1e	(Paul et al., 2006)
1f	(Daniel et al., 2012)
1g	(Suhong et al., 2005)
1h	(Gilbert et al., 2010)
1i	(Shaohan et al., 2010)
1j	(Antony et al., 2008)
1k	(Canan et al., 2007)
1l	(Nada, 2008)
1m	(Injazz, Antony, & Augustine, 2004)
1o	(Mei & Qingyu, 2011)

Article Code	Article
1p	(Hojung, David, & Darryl, 2000)
1q	(Patricia, Soumen, & Nagesh, 2006)
1r	(Shawnee, Jayanth, Cornelia, & Roger, 2003)
1s	(Michael & Nallan, 2009)
1t	(Ganesh & Sarv, 2008)
1u	(Kenneth, Dwayne, & Anthony, 2008)
1v	(Prakash & Damien, 2009)

Appendix B - List of analysed empirical studies in journal group B

Article Code	Article
2a	(Adegoke & Andrew, 2012)
2b	(Kenneth, Dwayne, & Anthony, 2012)
2c	(Sang, DonHee, & Schniederjans, 2011)
2d	(Chinho et al., 2005)
2e	(Wing et al., 2008)
2f	(Suhong, Bhanu, Ragu-Nathan, & Subba, 2006)
3a	(Murugesan, Ponnusamy, & Ganesan, 2012)
3b	(Paul et al., 2010)
3c	(Sufian, Monideepa, & Ragu-Nathan, 2012)
3e	(Su & Chyan, 2010)cord></Cite></EndNote>
3f	(Wong, Kris, Hon, & Ngan, 2011)
3h	(Sonia, Ned, Ronaldo, & Jacques, 2012)
3i	(Nakano, 2008)
3j	(Gensheng & George, 2011)
3k	(Clifford, Theodore, & Terry, 2010)
3l	(Keah et al., 2010)
3m	(John, Glenn, Haozhe, & Scott, 2011)
3n	(Felix & Alain, 2013)>
3p	(Sezhiyan & Nambirajan, 2010)
3q	(Jonathan, Michael, & Ali, 2001)
3r	(Michael, 2004)