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SHARIF, Saeed Pahlevan, MOSTAFIZ, Imtiaz and GUPTAN, Vinitha

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Structural Equation Modeling in Nursing Research: A Systematic Review

Saeed Pahlevan Sharif[1*], Md Imtiaz Mostafiz[1], and Vinitha Guptan[1]

[1]Taylor's Business School, Taylor's University, Malaysia

[*]Corresponding Author: Saeed Pahlevan Sharif, saeed.sharif@taylors.edu.my

Abstract

Aim: To present a systematic review of nursing papers employing structural equation modeling.

Background: A growing number of nursing studies have used structural equation modeling analysis. However, there is a paucity of research that has assessed conducting structural equation modeling analysis in nursing papers.

Data sources: Five major nursing journals were searched, each from inception until the end of February 2016. A total of 205 papers were identified.

Review methods: A methodological review and critical evaluation of the papers was provided. A content analysis was carried out to identify how nursing scholars conducted structural equation modeling method.

Discussion: The results revealed poor reporting of information about sample size determination, missing data, normality, and outliers. The majority of the studies neither computed composite reliability nor assessed convergent and discriminant validity. There was a lack of consistency in performing the analysis. Some of the studies conducted exploratory factor analysis before performing confirmatory factor analysis without discussing its necessity. Although most of the studies declared the estimation method and software used, there were still a considerable number of papers that did not disclose this information.

Conclusions: Little information about different steps of conducting structural equation modeling analysis was provided in nursing papers. Several weaknesses and areas of improvement for future empirical SEM studies were identified.

Implications for research/practice: In conducting structural equation modeling, there are many issues that should be addressed. Overlooking these issues may question the validity of the findings. The results of this review provide nursing researchers with best-practice guidelines for conducting structural equation modeling and pave the way for researchers to adopt this method in their studies.

Keywords: structural equation modeling; confirmatory factor analysis; covariance-based; methodological review; model fit; nursing.

Introduction

During recent years, covariance-based structural equation modeling (SEM) has become enormously popular in social science research (Hair *et al* 2013). Nursing is not an exception and a considerable body of nursing literature has been formed by the results obtained from this technique. SEM is a multivariate technique that can be seen as a hybrid of factor analysis and path analysis (Kline 2015). Indeed, SEM can be used to simultaneously examine a set of relationships between observed (directly measured, e.g. blood pressure) and latent variables (not directly measured, e.g. quality of care). There are several software packages for SEM which are mainly different in terms of their graphical interface and results presentation. The main differences between the packages include the user interface, capability to conduct multiple group analysis, and the availability of different options such as model fit indices that they provide (Narayanan 2012).

A growing number of studies in nursing research have applied SEM and this is increasing exponentially. However, there is a paucity of research that has assessed conducting SEM analysis in nursing studies. This study was conceived to fill this gap in the knowledge. Thus, this paper aimed to identify to what extent nursing researchers followed the guidelines and procedures recommended by the most prominent literature and methodological papers on SEM (Hair *et al* 2010, Anderson and Gerbing 1988, Byrne 2013, Ho 2013, Fornell and Larcker 1981, Meyers *et al* 2005, Tabachnick and Fidell 2012, Kline 2015). It is expected that the results of this critical systematic review would provide nursing researchers with best-practice guidelines for conducting SEM and pave the way for researchers to adopt high quality SEM in their studies.

Methods

A systematic review of nursing empirical papers that used SEM analysis was performed to identify how nursing scholars implemented SEM. This systematic review was conducted by following the reporting checklist of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Liberati *et al* 2009). All papers published in the five major nursing journals until the end of February 2016 were taken into consideration. These were: International Journal of Nursing Studies, Journal of Advanced Nursing, Journal of Clinical Nursing, Journal of Nursing Management, and Journal of Pain & Symptom Management. These five journals were among the top-tier nursing journals on Google Scholar Metrics with the highest number of empirical papers using SEM. This study acknowledges that focusing on these five journals may not be entirely representative of the body of knowledge in nursing studies. However, the findings would improve researchers' understanding of the SEM application in this field.

The search engine provided by the websites of the journals was used to search for papers published in the selected journals containing "structural equation model" keyword in their text while no date and language restrictions were imposed. All identified papers were carefully reviewed to exclude the papers that despite containing the keyword had not used SEM method. Next, a content analysis of the included papers was carried out to assess how SEM analysis was conducted in nursing studies. To do so, this study identified the main parts of conducting SEM analysis reported in the papers based on the criteria provided in Box 1.

> **Box 1. Extracted items from each included paper**
>
>
> **Model specification and data preparation**
>
>   Theoretical framework presentation
>
>   Sample size and its determination criteria
>
>   Detecting and handling outliers
>
>   Identifying and handling missing data
>
>   Assessing and handling multivariate normality
>
> **Measurement and structural model assessment**
>
>   Reporting estimation method
>
>   Reporting software package
>
>   Model fit assessment
>
>   Construct validity assessment
>
>   Model re-specification
>
>   Following a two-step approach (Anderson and Gerbing 1988)
>
>   Conducting bootstrapping

The choice of these twelve criteria was based on the guidelines and recommendations of the most prominent literature on structural equation modeling (Hair *et al* 2010, Anderson and Gerbing 1988, Byrne 2013, Ho 2013, Fornell and Larcker 1981, Meyers *et al* 2005, Tabachnick and Fidell 2012, Kline 2015), which contemplated the importance of considering these points while conducting SEM analysis. A data extraction sheet was developed and pilot-tested on 30 randomly-selected included papers. One of the authors extracted the above mentioned data from the selected studies and the second author checked the extracted data. Disagreements were resolved by consensus.
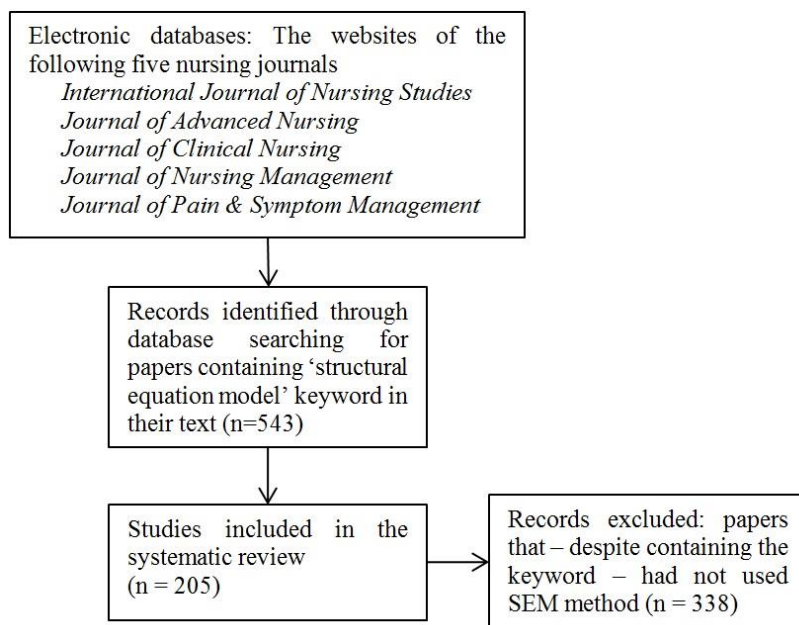
Results

The search results

The literature search resulted in 543 records in which 338 of them were eliminated as they did

not meet the eligibility criteria. Figure 1 shows the selection process used in this study. In total, 205 studies were included in this systematic review. The first paper was published in 1997 and the last included paper was published in February 2016. The search results also showed that after 2006 the growth rate of the number of papers using SEM outpaced the growth of the number of all published research papers. This indicates that using SEM method has become more popular during the past ten years.

Figure 1. Flow chart of the study selection process

Electronic databases: The websites of the following five nursing journals
   International Journal of Nursing Studies
   Journal of Advanced Nursing
   Journal of Clinical Nursing
   Journal of Nursing Management
   Journal of Pain & Symptom Management

Records identified through database searching for papers containing 'structural equation model' keyword in their text (n=543)

Studies included in the systematic review (n = 205)

Records excluded: papers that – despite containing the keyword – had not used SEM method (n = 338)

SEM in Nursing Studies

A summary of the research findings is reported in Table 1. As it is shown, 170 SEM papers (82.93%) presented their theoretical framework. The mean of the sample size used in all SEM papers was 622.83 (SD = 1403.6, range = 53 to 16,707). More than 70% of the papers used a sample size between 100 and 500. The mean and median of the sample sizes used in the articles after excluding the extreme cases were 455.84 and 342.00 respectively (SD = 359.53). The average sample size increased over time from 378.25 in the years between 1997 and 2000 and reached to 600.56 in 2016. Among them, 48 papers (23.41%) justified their sample size and 51 articles (24.88%) reported the frequency and/or the percentage of their missing cases. Handling missing cases was discussed in 56 papers (27.32%). Thus, only about a quarter of the selected papers explained about sample size determination and their missing data.

The selected papers showed a lower level of disclosure of information about normality. Less than 10% of the papers assessed specifically univariate (8 papers, 3.90%) and multivariate (20 papers, 9.76%) normality. Thirty one papers (15.12%) mentioned normality without distinguishing univariate from multivariate normality. Sixteen papers (7.80%) reported how they handled non-normality cases. The majority of the papers were not transparent about outliers and only 11 papers (5.37%) reported how they detected and handled outliers.

Table 1. Summary of findings

Category	Criteria	Time period				
		1997-2000	2001-2005	2006-2010	2011-2016	1997-2016
	Number of published papers	8	16	67	92	205
	Theoretical framework	5(62.50%)	11(68.75%)	52(77.61%)	83(90.22%)	170(82.93%)
Data	Sample Size					
preparation	Minimum	109	56	102	53	53[a]
	Maximum	1430	787	1485	16707	16707[a]
	Average	378.25	269.19	451.70	790.21	622.83[a]
	Standard deviation	437.14	194.45	286.72	1850.43	1403.58[a]
	Sample size determination	2(25.00%)	0(0.00%)	19(28.36%)	20(21.74%)	48(23.41%)
	No. or % of missing data	1(12.50%)	4(25.00%)	12(17.91%)	29(31.52%)	51(24.88%)
	Handling missing data	2(25.00%)	2(12.50%)	13(19.40%)	33(35.87%)	56(27.32%)
	Univariate normality	0(0.00%)	1(6.25%)	1(1.49%)	4(4.35%)	8(3.90%)
	Multivariate normality	1(12.50%)	2(12.50%)	6(8.96%)	7(7.61%)	20(9.76%)
	Generally mentioning normality	1(12.50%)	2(12.50%)	12(17.91%)	14(15.22%)	31(15.12%)
	Handling non-normality	0(0.00%)	3(18.75%)	4(5.97%)	6(6.52%)	16(7.80%)
	Univariate outliers	0(0.00%)	0(0.00%)	2(2.99%)	2(2.17%)	4(1.95%)
	Multivariate outliers	0(0.00%)	0(0.00%)	1(1.49%)	3(3.26%)	5(2.44%)
	Generally mentioning outliers	0(0.00%)	2(12.50%)	1(1.49%)	1(1.09%)	5(2.44%)
	Handling outliers	0(0.00%)	2(12.50%)	3(4.48%)	5(5.43%)	11(5.37%)
Reliability and	Cronbach's alpha	8(100%)	16(100%)	65(97%)	110(96.49%)	199(97.07%)
construct	Factor loadings	5(62.50%)	4(25.00%)	32(48.00%)	47(41.23%)	88(42.93%)
validity	Composite Reliability	0(0.00%)	1(6.00%)	11(16.00%)	19(16.67%)	31(15.12%)
Assessment	Average variance extracted	0(0.00%)	0(0.00%)	6(9.00%)	8(7.02%)	14(6.83%)
	Convergent validity	2(25.00%)	1(6.00%)	12(18.00%)	18(15.79%)	33(16.10%)
	Discriminant validity	1(12.50%)	1(6.00%)	11(16.00%)	20(17.54%)	33(16.10%)
	Maximum shared squared variance	0(0.00%)	0(0.00%)	1(1.00%)	1(0.88%)	2(0.98%)
	Average shared square variance	0(0.00%)	0(0.00%)	1(1.00%)	0(0.00%)	1(0.49%)
	Other forms of validity	0(0.00%)	3(19.00%)	7(10.00%)	5(4.39%)	15(7.32%)

Table 1. (continued)

Category	Criteria	Time period				
		1997-2000	2001-2005	2006-2010	2011-2016	1997-2016
Measurement	Conducting EFA	2(25.00%)	2(12.50%)	22(32.84%)	23(20.18%)	49(23.90%)
and structural	Conducting CFA	5(62.50%)	3(18.75%)	48(71.64%)	81(71.05%)	137(66.83%)
model	Re-specification in CFA	2(25.00%)	1(6.25%)	22(32.84%)	46(40.35%)	71(34.63%)
assessment	Conducting bootstrapping	0(0.00%)	2(12.50%)	5(7.46%)	22(19.30%)	29(14.15%)
	Estimation method					
	Maximum likelihood	3(37.50%)	8(50.00%)	38(56.72%)	65(57.02)%	114(55.61%)
	Weighted least squares	1(12.50%)	0(0.00%)	0(0.00%)	6(5.26%)	7(3.41%)
	Stepwise least robust	0(0.00%)	0(0.00%)	0(0.00%)	1(0.88%)	1(0.49%)
	Not reported	4(50.00%)	8(50.00%)	29(43.28%)	42(36.84%)	83(40.49%)
	Software Package					
	AMOS	1(12.50%)	5(31.25%)	30(44.78%)	57(50.00%)	93(45.37%)
	LISREL	2(25.00%)	6(37.50%)	21(31.34%)	22(19.30%)	51(24.88%)
	MPLUS	0(0.00%)	0(0.00%)	0(0.00%)	18(15.79%)	18(8.78%)
	SAS	1(12.50%)	0(0.00%)	0(0.00%)	0(0.00%)	1(0.49%)
	EQS	4(50.00%)	0(0.00%)	7(10.45%)	3(2.63%)	14(6.83%)
	Others	0(0.00%)	0(0.00%)	1(1.49%)	2(1.75%)	3(1.46%)
	Not Reported	0(0.00%)	5(31.25%)	8(11.94%)	12(10.53%)	25(12.20%)
The most	Chi-square, *df*, *p*-value	5(62.50%)	11(68.75%)	62(93.00%)	103(90.35%)	181(88.29%)
commonly	CFI	2(25.00%)	6(37.50%)	43(64.00%)	94(82.46%)	145(70.73%)
used model fit	RMSEA	1(12.50%)	7(43.75%)	52(78.00%)	77(67.54%)	137(66.83%)
indices	CMIN/DF	2(25.00%)	5(31.25%)	22(33.00%)	51(44.74%)	80(39.02%)
	SRMR	2(25.00%)	1(6.25%)	23(34%)	40(35.09%)	66(32.20%)
	GFI	1(12.50%)	6(37.50%)	23(34.00%)	34(29.82%)	64(31.22%)
	NFI	2(25.00%)	1(6.25%)	22(33.00%)	21(18.42%)	46(22.44%)
	AGFI	1(12.50%)	7(43.75%)	18(27.00%)	19(16.67%)	45(21.95%)
	IFI	1(12.50%)	3(18.75%)	11(16.00%)	23(20.18%)	38(18.54%)
	TLI	0(0.00%)	0(0.00%)	7(10.00%)	24(21.05%)	31(15.12%)
	NNFI	2(25.00%)	1(6.25%)	12(18.00%)	13(11.40%)	28(13.66%)

Note: EFA: exploratory factor analysis; CFA: confirmatory factor analysis; CFI: comparative fit index; RMSEA: root mean square error of approximation; CMIN/DF: the minimum discrepancy/degrees of freedom; SRMR: standardized root mean square residual; GFI: goodness-of-fit index; NFI: normed fit index; AGFI: adjusted goodness-of-fit index; IFI: incremental fit index; TLI: Tucker-Lewis index; NNFI: non-normed fit index.
[a]Descriptive statistics of the sample sizes after excluding the extreme cases: minimum = 53, maximum = 2221, mean= 455.84, median= 342.00, and standard deviation = 359.53.

The results revealed that in order to assess reliability, while 199 papers (97.07%) computed Cronbach's alpha, only 31 papers (15.12%) used composite reliability. Less than half of the articles (88 papers, 42.93%) reported factor loadings. Also, 33 papers (16.10%) assessed convergent and discriminant validity and 14 papers (6.83%) computed average variance extracted (AVE) of each construct. In total, 24.24% of the papers that assessed discriminant validity cited Fornell and Larcker (1981). Other forms of validity, such as content validity and face validity were assessed in 15 papers (7.32%). Assessing construct reliability, convergent validity, and discriminant validity became more prominent from 2008 onwards although it was not practiced by the majority of the papers.

Before running confirmatory factor analysis (CFA) and SEM, 49 papers (23.90%) performed exploratory factor analysis (EFA). However, over the years, the number of papers performing EFA has reduced and reached to only 2 papers in 2014 and 2 papers in 2015. 137 articles (66.83%) conducted CFA. Among them, 71 papers re-specified their model (e.g. deleting indicators or correlating the measures error terms) to improve the model fit. Moreover, 29 articles (14.15%) performed bootstrapping. Seventeen papers reported number of resamples in which bootstrapping with 1000 resamples was the most popular one (47.06%) followed by 5000 resamples (23.53%). Conducting bootstrapping has become more common in the past few years.

The majority of the articles used maximum likelihood as the estimation method (114 papers, 55.61%). AMOS was the most common software package used (93 papers, 45.37%) followed by LISREL (51 papers, 24.88%) and MPLUS (18 papers, 8.78%). While using AMOS and Mplus is growing over the years, the number of studies that used LISREL and EQS are decreasing so that no papers used EQS after 2012 and in the last two years employing LISREL was limited to one paper per year.

Chi-square was the most commonly used index to assess model fit reported by 181 papers (88.29%) followed by comparative fit index (CFI; 145 papers, 70.73%) and root mean square error of approximation (RMSEA; 137 papers, 66.83%). After 2005, while researchers' tendency to report nonnormed fit index (NNFI), adjusted goodness of fit index (AGFI), normed fit index (NFI), and Goodness-of-fit index (GFI) reduced, using CFI, and Chi-square/df increased. Moreover, referring to Tucker–Lewis index (TLI) is growing over time.

Discussion

This study was conducted to provide a critical evaluation of the empirical papers published in nursing journals that used SEM. By reviewing 205 papers published in the five of the top-tier nursing journals, several weaknesses and areas of improvement for future nursing studies were identified. The content analysis of the papers showed that about a quarter of the papers provided information on sample size determination, and missing data. Moreover, the results revealed that a small number of studies assessed normality and outliers. Cronbach's alpha was the most common used method to evaluate reliability. The majority of the studies neither computed composite reliability nor assessed convergent and discriminant validity. Few studies computed AVE, maximum shared squared variance, and average shared square variance. There was a lack

of consistency in performing the analysis. While some studies performed EFA, most of them skipped EFA in favor of CFA. Although most of the papers declared the estimation method and the software used, there were still a considerable number of papers that did not disclose this information. To address these weaknesses, the following suggestions are made.

Future studies are recommended to justify their sample size and disclose more information about missing data, multivariate normality, and outliers. Generally, SEM is a large sample size technique. The minimum required sample size depends on the desired power (see SEM power estimation on RMSEA method, MacCallum, Browne, and Sugawara, 1996; on bootstrapping method, Satorra and Saris, 1985 and Yung and Bentler, 1999; and on Monte Carlo simulation, Muthén and Muthén, 2002), the size and complexity of the model, score characteristics, and distribution of the data (MacCallum *et al* 1996, Weston and Gore 2006, Ullman 2006). Although some researchers argue that model fit is very sensitive to sample size (Jackson 2003, Jackson 2001), using a large sample size is most often recommended in the literature (MacCallum *et al* 1996). Moreover, both univariate outliers (see Tukey 1977, Hoaglin *et al* 1986, Hoaglin and Iglewicz 1987) and multivariate outliers (Byrne 2013) should be assessed as they may influence the results and reduce the generalizability of the findings. Also, multivariate normality is one of the assumptions of Maximum likelihood. Multivariate non-normality may bias model fit statistics, standard errors and parameter estimates.

In performing the analysis, we suggest researchers to follow a two-stage approach including (i) conducting CFA and assessing the model fit, and (ii) performing SEM and testing the hypotheses. However, when researchers have little ideas about how the items are structured or previous studies on the factor structure are inconclusive, it is recommended to perform an EFA first (Anderson and Gerbing 1988, Matsunaga 2010, Pahlevan Sharif and Mahdavian 2015). This paper also suggests future researchers to assess reliability using composite reliability as well as coefficient H and/or coefficient omega. As Cronbach's Alpha assumes equal factor loadings or error terms among all indicators, it provides a less accurate measure of construct reliability than the suggested methods (Chin 1998). Convergent validity (i.e. items correlate highly with the construct they measure) and discriminant validity (i.e. items do not correlate highly with the items of other constructs) needs to be evaluated as well (Hair *et al* 2010, Nunnally and Bernstein 1994, Fornell and Larcker 1981). All factor loadings and AVE (i.e. the average amount of variance in items that a construct explains) should be computed although assessing convergent validity using AVE may be too conservative (Malhotra and Dash 2011). Researchers are suggested to justify the estimation method used in their study. While since the inception of SEM, maximum likelihood has been the predominant estimation method, there are other methods that do not assume multivariate normality (e.g. weighted least squares) (Anderson and Gerbing 1988). Moreover, the software package used should be declared.

There are plenty of model fit indices, each is developed to address a slightly different objective. They can be grouped into three categories including absolute (how well a hypothesized model fits observed data), incremental (the relative position of the model between worst to perfect fit), and parsimonious fit (to what extent a model value parsimony) (Hair *et al* 2010, Ho 2013, Jaccard and Wan 1996, Meyers *et al* 2005). Referring to five fit indices including chi-square, its respective *df*, and *p*-value, RMSEA and its associated confidence intervals or SRMR, and at least two incremental fit indices provides more confidence in the model fit (Kline 2015, Meyers *et al* 2005, Thompson 2004). Re-specifying the model to improve

the model fit must have theoretical support. Otherwise, researchers may 'overfit' the model which diminishes its generalizability. Moreover, estimating the standard errors using bootstrapping is recommended. Bootstrapping is a non-parametric method, relying on random sampling with replacement that makes no distributional assumptions of variables and would estimate more reliable standard errors and confidence intervals (Dijkstra 2010).

This review is not without limitations. Although efforts were made to ensure that all SEM studies published in the selected journals to be included, it is possible that some papers have been missed. Selecting five nursing journals may not be entirely representative of all nursing studies that conducted SEM analysis. Also, reporting standards of other journals may differ. Moreover, the SEM issues that should be addressed are not limited to those that were discussed in this study although this methodological review has been relatively comprehensive.

Conclusion

This descriptive methodological study critically reviewed empirical papers that used SEM and were published in five of the top nursing journals to assess to what extent nursing scholars followed the guidelines of the most prominent literature on SEM. In conducting SEM, there are many issues that should be addressed. Indeed, overlooking these issues may question the validity of the findings. The results of this study revealed that little information about different steps of conducting the analysis was provided in nursing papers. Several weaknesses were identified and the major implications for future empirical SEM studies were subsequently discussed.

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