Journal of Physics: Conference Series

PAPER • OPEN ACCESS

Gain More Insight from Common Latent Factor in Structural Equation Modeling

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Abstract. There is a great deal of evidence that method bias is really sure influences item validities, measurement error, correlation and covariance between latent constructs and thus leading the researchers to erroneous conclusion due to inflation or deflation during hypothesis testing. To remedy this, the study provides a guideline to minimize the method bias in the context of structural equation modeling employing the covariance method (CB-SEM) using medical tourism model. A practical approach is illustrated for the identification of method bias based on the new construct namely common latent factor. Using this latent construct, we managed to identify which item has potential to permeate more variance from common latent factor. Nevertheless, we figure out that the method bias is do not exist in our developed model. Therefore, this measurement model is appropriate for structural model in order to achieve the research hypotheses. We hope that this discussion will help the researchers anticipate which items are likely exposed on method bias before proceed to advance modeling.

Keywords: Method Bias, Common Latent Factor, Covariance Method, Structural Equation Modeling.

1. Introduction
There has been a germination of Structural Equation Modeling (SEM) in information system [1], entrepreneurship [2], tourism [3, 4, 5], social sciences [6,7], marketing [8, 9], management [10,11,12] and other fields [13, 14, 15]. The method of path analysis has been developed by Wright and has been modified in 1960 to study the causal relationship between exogenous and endogenous constructs [16].

Applied researchers have hold the SEM ability to model the complex modeling that consists of numerous reflective and formative measurement models, correcting the measurement error, specify model through modification index and estimate parameter of all theories simultaneously. There are two families of SEM have been penetrated in various areas such as Covariance or Common factor based SEM (CB-SEM) and Variance or Partial Least Square based SEM (PLS-SEM) but both methods are suggested should be applied in different situations whether in the confirmatory or exploratory research. [9] and [15] suggested that CB-SEM or traditional SEM is suitable for confirmatory testing or theory driven, while PLS-SEM is preferable for exploratory research.

In the areas of marketing and social sciences, the questionnaire is the prominent tool for data collections where most of the published researches is about the perception, attitude, characteristics, behavior, opinion and any related to social phenomenon. [17] and [18] put forth that these latent construct are measured indirectly through manifest variable that generally known as items that can be perceived from the question exhibited. Usually, indicator values are classified as numeric scales or continuous scale and thus suit for handling the parametric testing. In developing the questionnaire phase is very important to ensure the goal of the particular research can be achieved [19]. However, there are very lack of studies to discuss the main problem that might has a potential to affect the parameter estimates especially in tourism studies. They are more likely incline to ensure the research hypothesis can be obtained using the various advance statistical method rather than to ensure the model involved are reliable for hypothesis testing.

Although the previous study disclosed the effect of common method bias has a great prospect to undermine the true probability score but this method remains infrequently promoted in social sciences researches. In this paper, we provide a discussion regarding the common method bias with traditional SEM using medical tourism model. At this level, we also demonstrate the guidelines to handle the common method bias using common latent factor since this procedure is apparently more relevant compare to conventional approach of Harman Single Factor [20, 21]. In additions, there are less published research paper to provide a guideline about common latent factor to minimize the detrimental effect. In part of this, we assume that many applied researchers are not well understood about the effect of common method bias. So, we model three latent constructs namely Service Quality, Physical Infrastructure and Patient Satisfaction with four indicators. This model is treated as first order construct and using the Maximum Likelihood Estimator and Expectation Maximization algorithm to obtain the parameter estimates [22].

In further discussion, we entail the standardized estimate in order to obtain the factor loading for every item in a model. In view of this, the current paper contributes to the literature by: a) examining the quality of measurement model using pooled confirmatory factor analysis, b) identifying the potential common method bias among the items with guideline to control it, and c) suggesting several recommendations that can be used to diminish it. Hopefully, this information will provide researchers, academician, practitioners, and readers with better tools and guidelines to minimize the detrimental effects of common method bias.

2. Common Method Bias

The threat of the effect of common method bias have long been discussed in the previous research [23, 24, 25, 26, 27, 28]. Among these literatures, [29] and [30] contemplated that any measuring instrument inevitably has systematic construct variance and systematic error variance due to the characteristics of the specific method being employed. He also defines the measurement process from the beginning phase of which the content of item, the response format, instruction given, the characteristics of examiner, capability of respondent and respondent motivation are the reason of why the method bias occurred. For instances, the instruction at the top questionnaire may influence the answer provided and thus leading them fail to answer accurately.

In some cases, the respondent might have confused about the aim of the question exhibited due to ambiguity statement or double-barreled questions. This situation decreases the ability of respodent to generate an accurate response [31, 32] and thus leading them to rely on stylistic response tendencies [33, 34]. For double-barreled questions are occurred when two different subjects are asked in a same question to answer [35, 36, 25]. These reasons cause the indicators to share a certain amount of common variation that become one of detrimental effect to influence the covariation estimate, correlation estimates, inflation, deflation or may no effect on the causal effect during the inferential process [37, 38].

Because of this effect, many reviewers are concerns about the common method bias during the review process [39, 40]. During the confirmatory factor analysis phase, the covariation and correlation can be estimated wrongly due to the method bias. Because common method bias has a capability to increase or decrease the standardized estimate and thus leading to the inflation or deflation. In hypothesis testing, there are two type error has been introduced namely Type 1 error and Type II error rates. Inflated in path estimate, covariation, correlation and factor loading increase the danger of Type 1 error (false positives), which means that an effect may be considered has significant effect even though it is actually does not exist in the real population [41, 42, 43]. To contrast, deflation in path estimate, covariation, correlation and factor loading potentially leading to Type II error (false negative), which means that an effect may considered not significant even though it does not actually present in the real population [44]. In social science and other related field, [45] pointed out that false positive is often regarded as a more severe problem than false negative. Therefore, this is the reason why confidence levels of 95% or higher are always required in determining the hypothesis testing.

This severe problem is always distressing among the researchers to obtain the true finding. If the false positive is really happening in research, their finding would be affected and subsequent leading them to draw the conclusion in wrong path. The wrong conclusion is totally waste for those who expend their effort and money to conduct their research grant. To clarify some aspects of its nature, we adopt common latent factor to capture the common variance among all observed variables in the model. To do this, only traditional SEM has a capability to handle this method very well that has been implemented in some software such as AMOS, LISREL, MPLUS, EQS and so forth. Moreover, this particular method can be proper conducted during the confirmatory factor analysis.

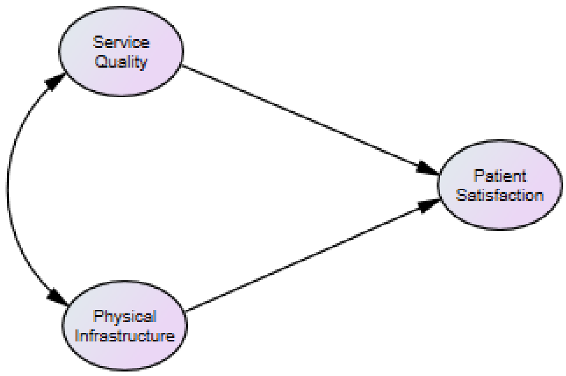

Figure 1: Illustrative Model

In our questionnaire, we have four items or manifest variable for each latent constructs (Service Quality, Physical Infrastructure, and Patient Satisfaction). Means that, we have 12 items developed that will be evaluated in this process began with unidimensional procedure until the fitness index meet the requirement as presented in Figure 2.

Mathematically, there are two types of equation that might be involved in measurement model. If the measurement model is not contaminated of with common method bias, each of the four indicators X_{ij} would be derived from its first latent construct F_i of which have three main construct according to Equation (1) based on [46]:

$$X_{ij} = \lambda_{ij} F_i + w_{\theta j} \theta_{ij}, I = 1,..3, j = 1,2,...6. \quad (1)$$

When θ_{ij} and F_i are assumed uncorrelated:

$w_{\theta j} = \sqrt{1} - \lambda ij^2$

Where:

λ_{ij} = Loadings of indicator

θ_{ij} = Standardised indicator error term

$w_{\theta j}$ = Weight of θ_{ij}

If the measurement model contaminated with common method bias, each of the seven indicators X_{ij} would be derived from its latent variable F_i according to (2), where M is included in the full Equation (1). So, the Equation (2) is presented as following:

$$X_{ij} = \lambda_{ij} F_i + w_M M + w_{\theta j} \theta_{ij}, I = 1,.3, j = 1,2,...6. \quad (2)$$

When θ_{ij} and F_i are assumed uncorrelated:
$w_{\theta j} = \sqrt{1} - \lambda ij^2$ - w_M^2
Where:
M = Standardized variable that represent for common method variation
w_M = Common method weight

The term $w_M M$ is represent as common variation that is shared by all indicators in the model. Since latent variables aggregate indicator in CB-SEM, we develop a new latent construct to our CFA model and impose it to all the observed variable in the measurement model as presented in Figure 3.

3. Confirmatory Factor Analysis

In CB-SEM, the confirmatory factor analysis is always required to confirm the measurement model for hypothesis testing besides to improve the quality of the model. Consequently, we model three first latent constructs (Service Quality, Physical Infrastructure, and Patient Satisfaction). Beforehand, we got 300 returned questionnaires with answers provided on Likert Scale (One of the psychometric scale) going from 1 to 10 (Strongly disagree to strongly agree).

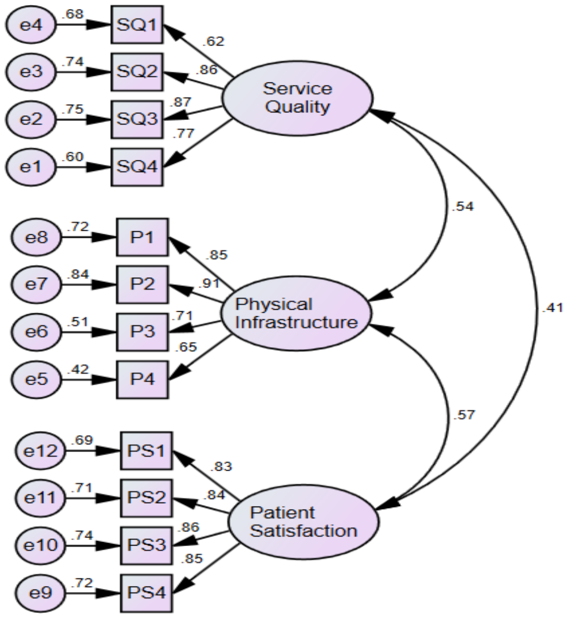

Figure 2: Confirmatory Factor Analysis

Thus, 300 questionnaires have been imported in SPSS file. In this stage, we have to delete the item that typically having lower than 0.60 of factor loading from once at a time. The process is repeated until the fitness is achieved as exhibited in Figure 2. From this analysis, all fitness such as RMSEA = 0.058; CFI = 0.979; TLI = 0.972; GFI = 0.959 and Chisq/df = 1.761 are meet the required level. However, this finding is inadequate for us to ensure that this measurement model is not affected by method bias. Thereby, we entail the common latent factor to handle this matter as we explain the guideline later.

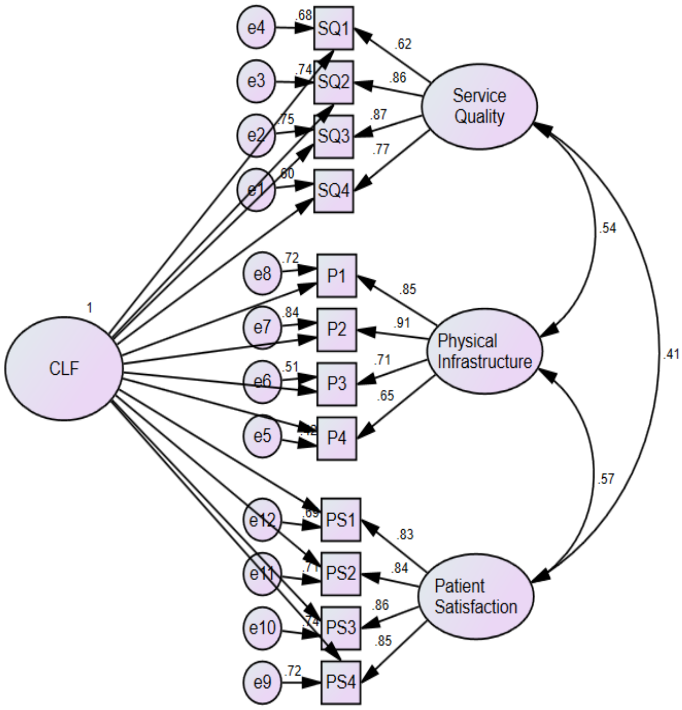

Figure 3: Common Latent Factor

Figure 3 illustrates that all observations have being exerted by one latent construct namely CLF. CLF is an acronym for Common Latent Factor to represent as the common variation in this measurement model. The variance of CLF is constraint as '1' and the single headed arrow from this particular construct will be imposing on all observation in a model. Variance should be equal to 1.0 in which equivalent to 100 percent of total variation that has been explained by this construct (CLF). As such, the total variance can share its variance with all observation involved in measurement model. Using this step, we managed to identify which item has potential to permeate more variance from CLF construct.

Then, the applied researchers need to compare the standardized regression weight from constraint and unconstraint model. The standardized result from Amos default and paste on the Microsoft Excel. Afterwards, the estimate without CLF is minus to estimate with CLF to get the estimate difference. If the difference between them is larger than 0.2, then we can retain the CLF construct in a model [47]. In this case, we find out that the method bias is not exist in medical tourism model since all the observation are below that threshold value as enumerated in Table 1. Therefore, we can proceed to testing the hypothesis.

Table 1: Standardized regression Weight

Standardized Regression Weight			**Estimate With CLF**	**Estimate No CLF**	**Diff**
SQ1	←	Service Quality	0.674	0.626	0.048
SQ2	←	Service Quality	0.865	0.861	0.004
SQ3	←	Service Quality	0.882	0.871	0.011
SQ4	←	Service Quality	0.772	0.768	0.004
P1	←	Physical Infrastructure	0.871	0.853	0.018
P2	←	Physical Infrastructure	0.905	0.899	0.006
P3	←	Physical Infrastructure	0.710	0.705	0.005
P4	←	Physical Infrastructure	0.668	0.655	0.013

PS1	←	Patient Satisfaction	0.839	0.828	0.011
PS2	←	Patient Satisfaction	0.843	0.833	0.01
PS3	←	Patient Satisfaction	0.878	0.866	0.012
PS4	←	Patient Satisfaction	0.865	0.851	0.014

From the beginning, we aimed to provide a guideline to perform the common method bias using common latent factor. To date, there are many published papers already discusses about the severe problem due to the detrimental effect of method bias but the procedure in handling this matter still lacking. Using this method, we can justify that this measurement model is safe from an expose of method bias.

4. Discussion and Conclusion

The purpose of this paper has threefold objective as follows: a) examining the quality of measurement model using pooled confirmatory factor analysis, b) identifying the potential common method bias among the items with guideline to control it, and c) suggesting several recommendations that can be used to diminish it. More specifically, we managed to achieve all research objective by employing common latent factor in the context of structural equation modeling. Previously, we already informed about the capability of Harman single factor in minimizing the method bias. However, this method is seeming outdated and inappropriate for current development [48]. Using common latent factor, we are not only stay informed about the present of method bias but we managed to identify which items has potential to bring bias. Although it perceived more powerful to identify of the method bias, but, this procedure only applicable for covariance structure.

As has been addressed in many previous research, CB-SEM connotes as covariance based structural equation modeling tended to minimize the discrepancy between the estimated and observed data [7]. So, it is inevitably that the detrimental effect of method bias is always occurred due to the shared variance and thus effect to the convergent and discriminant validity. Hence, the latent variable correlation between constructs sometimes tended to inflation or deflation estimates. However, this severe problem is always neglected by academicians recently because they more likely to focus the variety of research method without concerns on precision and accuracy of parameter estimates obtained.

As a matter of facts, method bias must be concerned using established statistical method after evaluating the measurement models [49, 50]. In particular, [27] and [31] had provide several suggestions to avoid or minimizing the method bias during data collection. In this case, we already concern about the questionnaire validity and employing of statistical method in the context of structural equation modeling. Therefore, we can reasonably conclude that our illustration of the common latent factor discussed here is conventional in its demonstration and the guidelines provided is ease for the beginner in empirical research.

In the future research, we attempt to include more latent construct that related with the medical tourism model. That is, we can determine whether the increasing of latent constructs and items influences the present of method bias. Moreover, we might attempt to the latest method namely marker variable since its application being told more powerful than common latent factor. Thus, we could compare the two statistical methods between common latent factor and marker variable in terms of their effectiveness and sufficiency.

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