Gain More Insight from Common Latent Factor in Structural Equation Modeling

1Asyraf Afthanorhan, 2Zainudin Awang, 3Norliana Abd Majid, 4Hazimi Foziah, 5Izzat Ismail 6Hussam Al Halbusi, 7Shehnaz Tehseen

1,2,3,4,5 Faculty of Business and Management, Universiti Sultan Zainal Abidin Gong Badak, 6 University of Malaya, Faculty of Business and Accountancy 7 Department of Management, Sunway University

1E-mail: asyrafafthanorhan@unisza.edu.my

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] contemlated 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 responen 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.

![Illustrative Model](image)

**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]:

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

When $\theta_{ij}$ and $F_i$ are assumed uncorrelated:

$$w_{ij} = \sqrt{T - \lambda_{ij}^2}$$

Where:

$\lambda_{ij} =$ Loadings of indicator  
$\theta_{ij} =$ Standardised indicator error term  
$w_{ij} =$ Weight of $\theta_{ij}$

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

$$X_{ij} = \lambda_{ij} F_i + w_{Mj} M + w_{ij} \theta_{ij}, \quad I = 1,3, \quad j = 1,2,\ldots,6.$$  \hspace{1cm} (2)
When $\theta_{ij}$ and $F_i$ are assumed uncorrelated:

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

Where:

$M =$ Standardized variable that represent for common method variation

$w_M =$ Common method weight

The term $w_M$ 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](image)

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 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.

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

References
[1] Toma, L., Barnes, A. P., Sutherland, L. A., Thomson, S., Burnett, F., & Mathews, K. (2018). Impact of information transfer on farmers’ uptake of innovative crop technologies: a structural equation model applied to survey data. The Journal of Technology Transfer, 43(4), 864-881.
[2] Hoque, A. S. M. M., Awang, Z. B., Siddiqui, B. A., & Sabiu, M. S. (2018). Role of Employee Engagement on Compensation System and Employee Performance Relationship among Telecommunication Service Providers in Bangladesh. *International Journal of Human Resource Studies, 8*(3), 19-37.

[3] Afthanorhan, A., Foziah, H., Rusli, R., & Khalid, S. (2019). Modeling reflective constructs in generalized structure component analysis: An application to service quality and customer satisfaction in UniSZA library. *International Journal of Innovation, Creativity and Change, 7*(10), 33-41.

[4] Afthanorhan, A., Awang, Z., & Fazella, S. (2017). Perception of Tourism Impact and Support Tourism Development in Terengganu, Malaysia. *Social Sciences, 6*(3), 106.

[5] Afthanorhan, A., Awang, Z., Salleh, F., Ghazali, P., & Rashid, N. (2018). The effect of product quality, medical price and staff skills on patient loyalty via cultural impact in medical tourism. *Management Science Letters, 8*(12), 1421-1424.

[6] Markus, K. A. (2012). Principles and Practice of Structural Equation Modeling by Rex B. Kline. *Structural Equation Modeling: A Multidisciplinary Journal, 19*(3), 509-512.

[7] Majid, N. A., Zainol, F. A., Wan Daud, W. N., & Afthanorhan, A. (2019). Cooperative entrepreneurship in Malaysian secondary schools: A review of current practices. *Journal of Social Sciences Research, 5*(3), 812-818. doi:10.32861/jssr.53.812.818.

[8] Kashif, M., Samsi, S. Z. M., Awang, Z., & Mohamad, M. (2016). EXQ: measurement of healthcare experience quality in Malaysian settings: A contextualist perspective. *International Journal of Pharmaceutical and Healthcare Marketing, 10*(1), 27-47.

[9] Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*(3), 414-433.

[10] Awang, Z. H., & Jusoff, K. (2009). The effects of corporate reputation on the competitiveness of Malaysian telecommunication service providers. *International Journal of Business and Management, 4*(5), p173.

[11] Darwas, R., Syukhri, Wulandari, A., & Afthanorhan, A. (2020). Level of student satisfaction with laboratory facilities using the importance performance analysis (IPA) method. *Journal of Advanced Research in Dynamical and Control Systems, 12*(3), 195-201. doi:10.5373/JARDCS/V12I3/20201182

[12] Rahlin, N. A., Awang, Z., Afthanorhan, A., & Aimran, N. (2019). The art of covariance based analysis in behaviour-based safety performance study using confirmatory factor analysis: Evidence from SMES. *International Journal of Innovation, Creativity and Change, 7*(10), 351-370.

[13] Iskamto, D., Ghazali, P. L., Afthanorhan, A., Sukono, & Bon, A. T. (2019). Effect contextual factor toward entrepreneurial intention among young educated. Paper presented at the Proceedings of the International Conference on Industrial Engineering and Operations Management, 0(November) 413-419.

[14] Aimran, A. N., Ahmad, S., Afthanorhan, A., & Awang, Z. (2017a). The development of comparative bias index. In *AIP Conference Proceedings* (Vol. 1870, No. 1, p. 060008). AIP Publishing.

[15] Aimran, A. N., Ahmad, S., Afthanorhan, A., & Awang, Z. (2017b). The assessment of the performance of covariance-based structural equation modeling and partial least square path modeling. In *AIP Conference Proceedings* (Vol. 1842, No. 1, p. 030001). AIP Publishing.

[16] Tarka, P. (2018). An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. *Quality & quantity, 52*(1), 313-354.

[17] Smith, M. (2017). *Research methods in accounting*. Sage.

[18] Xu, J., Fan, X., Du, J., & He, M. (2017). A study of the validity and reliability of the parental homework support scale. *Measurement, 95*, 93-98.
[19] Dalila, Latif, H., Jaafar, N., Aziz, I., & Afthanorhan, A. (2020). The mediating effect of personal values on the relationships between attitudes, subjective norms, perceived behavioral control and intention to use. *Management Science Letters, 10*(1), 153-162. doi:10.5267/j.msl.2019.8.007

[20] Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research, 69*(8), 3192-3198.

[21] Jakobsen, M., & Jensen, R. (2015). Common method bias in public management studies. *International Public Management Journal, 18*(1), 3-30.

[22] Byrne, B. M. (2013). *Structural equation modeling with AMOS: Basic concepts, applications, and programming.* Routledge.

[23] Arndt, J., & Crane, E. (1975). Response bias, yea-saying, and the double negative. *Journal of Marketing Research, 218-220.

[24] Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological bulletin, 56*(2), 81.

[25] Podsakoff, N. P., Whiting, S. W., Podsakoff, P. M., & Blume, B. D. (2009). Individual- and organizational-level consequences of organizational citizenship behaviors: A meta-analysis. *Journal of Applied Psychology, 94*(1), 122.

[26] Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. Annual review of psychology, 63, 539-569.

[27] Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

[28] Kline, R. B. (2015). *Principles and practice of structural equation modeling.* Guilford publications.

[29] Fiske, D. W. (1982). Convergent-discriminant validation in measurements and research strategies. *New Directions for Methodology of Social & Behavioral Science.*

[30] Antonakis, J., & Day, D. V. (Eds.). (2017). The nature of leadership. *Sage publications.*

[31] MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: causes, mechanisms, and procedural remedies. *Journal of Retailing, 88*(4), 542-555.

[32] MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly, 35*(2), 293-334.

[33] Krosnick, J. A. (1991). Response strategies for coping with the cognitive demands of attitude measures in surveys. *Applied Cognitive Psychology, 5*(3), 213-236.

[34] Hulland, J., Baumgartner, H., & Smith, K. M. (2018). Marketing survey research best practices: evidence and recommendations from a review of JAMS articles. *Journal of the Academy of Marketing Science, 46*(1), 92-108.

[35] Bradburn, N. M., Sudman, S., & Wansink, B. (2004). Asking questions: the definitive guide to questionnaire design--for market research, political polls, and social and health questionnaires. John Wiley & Sons.

[36] Krosnick, J. A. (2018). Improving question design to maximize reliability and validity. In *The Palgrave Handbook of Survey Research* (pp. 95-101). Palgrave Macmillan, Cham.

[37] Kock, N. (2015). One-tailed or two-tailed P values in PLS-SEM? *International Journal of e-Collaboration (IJeC), 11*(2), 1-7.

[38] Podsakoff, P. M., & Todor, W. D. (1985). Relationships between leader reward and punishment behavior and group processes and productivity. *Journal of Management, 11*(1), 55-73.

[39] Chan, D. (2009). So why ask me? Are self-report data really that bad. *Statistical and methodological myths and urban legends: Doctrine, verity and fable in the organizational and social sciences, 309-336.*

[40] Kühler, T., Landis, R. S., & Cortina, J. M. (2017). From the Editors: Establishing Methodological Rigor in Quantitative Management Learning and Education Research: The Role of Design, Statistical Methods, and Reporting Standards.
[41] Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. MIS Quarterly.

[42] Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of research in Marketing*, 26(4), 332-344.

[43] Spellman, B., Gilbert, E., & Corker, K. S. (2017). Open science: what, why, and how.

[44] Lakens, D., & Etz, A. J. (2017). Too true to be bad: When sets of studies with significant and nonsignificant findings are probably true. *Social Psychological and Personality Science*, 8(8), 875-881.

[45] Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Erlbaum.

[46] Kock, N. (2014). Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. *International Journal of e-Collaboration (IJeC)*, 10(1), 1-13.

[47] Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE transactions on professional communication*, 57(2), 123-146.

[48] Gaskin, J. (2011), "Common Method Bias", Gaskination's StatWiki. http://statwiki.kolobkreations.com

[49] Nasir, M. N. M., Mohamad, M., Ghani, N. I. A., & Afthanorhan, A. (2020). Testing mediation roles of place attachment and tourist satisfaction on destination attractiveness and destination loyalty relationship using phantom approach. *Management Science Letters*, 10(2), 443-454. doi:10.5267/j.msl.2019.8.026

[50] Mohamad, M., Afthanorhan, A., Awang, Z., & Mohammad, M. (2019). Comparison between CB-SEM and PLS-SEM: Testing and confirming the maqasid syariah quality of life measurement model. *Journal of Social Sciences Research*, 5(3), 608-614. doi:10.32861/jssr.53.608.614