Journal of Contemporary Issues in Business and Government Vol. 27, No. 2, 2021
https://cibg.org.au/
P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.02.005

The Performance of Modern PLS and Conventional SEM for Second Order Construct of Family Communication Pattern Model

ASYRAF AFTHANORHAN[1], AZIYAH ABU BAKAR[2], NAZIM AIMRAN[3], NORFADZILAH RASHID[4*]

[1,4*]Faculty of Business and Management, UniSZA, Malaysia
[2]Faculty of Communication and Media Studies, College University Poly-Tech Mara, Cheras, Kuala Lumpur, Malaysia
[3]Faculty of Computer and Mathematics, UiTM Shah Alam, Malaysia
[*]Corresponding Author
Email ID: nikmfadzilah@unisza.edu.my

Abstract: This paper is aims to determine the performance of modern Partial Least Square (PLS) and Conventional SEM in family research. As such, the adoption of Measurement of Family Communication became the subject for testing their effectiveness. Measurement of Family Communication Pattern is broadly used to assess the happiness of the family either happy or unhappy and it was frequently noted as one of the confirmatory research. It shows that the conventional SEM was better than modern PLS in the presence of the second-order construct.

Keywords: Family Communication Pattern, Second Order Construct, Confirmatory Factor Analysis (CFA), Conventional SEM, Modern PLS

INTRODUCTION

The use of Structural Equation Modeling (SEM) application in empirical research is not considered as a new phenomenon any longer as the ability of such a method ascertains the researchers to specify their model conveniently. As such, the structural equation modeling able to handle multiple variables, latent variables, complex relationships, complex correlations, and covariance simultaneously (Awang, 2015). Lately, structural equation modeling can be defined into two construct measurement. The first part was considered as the common factor and the second part was attributed as the composite factor. The current paper intends to use the measurement of the Family Communication Pattern as the main subject.

Communication within the family is an important and major aspect in determining the survival of the family was able to achieve happiness or not (Braithwaite et al., 2003). Many studies on the family found flaws in the family occurs due to the communication that did not function properly (Baxter, 2000). Communication within the family is very important for character building and personal development of children. Children are the reflection of their parents (Jusang, 2008). Therefore, only with communication, children will be informed of their responsibilities as children, peers, students, community members, employees, spouses and even as parents (Narimah, 2008).

Many studies that discussed aspects of family and communication, said that communication is a key element that will determine whether the family's happiness can be achieved or not. According to Ballard-Reisch and Weigel (2006), communication is a 'tool' that can measure happiness in the family. Therefore, an instrument for measuring communication within the family has been (was) formed to look at how family communication patterns ~~that~~ work and its impact on family members. The instrument for measuring family communication patterns have been (was) developed by McLeod and Chafee in 1973. Then it was modified by Ritchie and Fitzpatrick in 1990. As these instruments have been adopted many times by many researchers, however, it is important to study the testing instrument at the local level, especially using different locations and respondents.

Family communication pattern is consisting of two dimensions such as conformity and conversation orientation which one could ponder it is a second-order model. This model has been justified in many years but its potential never being tested with the second generation method like SEM. Specifically, SEM has two families: 1. Covariance based SEM or common factor model and 2. Variance based SEM or composite model. Both methods can test the path analysis with latent variable. Under the composite model, three types of approaches were successfully applied in various fields such as generalized structure component analysis, regression on sum scales, and partial least square. Among them, partial least square is the most fully developed and therefore its inception was improved to modern PLS which becoming more popular for confirmation technique. However, the study related to modern PLS and the common factor model in family research is none which motivates us to investigate the full potential of these methods when implementing the higher-order model.

The objective of this study is to determine the performance of modern Partial Least Square (PLS) when a common factor model is involved. Furthermore, the second-order construct was used as no research has ever been conducted clearly to analyze the performance of modern PLS. Finally, the variables of the measurement of the Family Communication Pattern and the findings are discussed.

LITERATURE REVIEW

Family Communication Patterns

Family communication pattern consists of two dimensions, namely conversation orientation, and conformity orientation. The orientation of the conversation, in which emphasizes family shaped two-way communication. Parents provide an opportunity for children to express their views, and together decide on issues that arise in the family. In other words, parents are more friendly, accommodating and providing support to children in any events and activities that their children want to do. While the orientation of conformity which emphasizes family in the form of one-way communication, where parents determine the rules that must be followed, by children. In other words, parents are firm, cold, less eager to cooperate and keep face (Ritchie et al., 1990).

Family communication patterns are referred to as the style of communication practiced in a family. Each family has a communication pattern. It depends, on the philosophy, beliefs, and views, of the family, about life. Therefore, the type of communication patterns within each family is different from one another (Koestan, 2004). For example, many studies in the West family said, most of the families there, practicing conversation orientation compared to the orientation of conformity (Dumlao et al., 2000; Allison, 2004; Koerner et al., 2004; Bexter et al., 2005). Western parents are more open in terms of outlook and compromise in many events and activities performed by their children. As a result, children in West family have confidence and high customization in their social life (Kelley et al., 2002; Koerner et al., 2004; Wilson et al., 2004; Wood, 2004).

On the contrary, many families in Asia, especially families in China and India, said most of the families prefer to practice communication in the form of conformity (Trubisky et al., 1991; Siu Man, 2002; Zhang et al., 2005; Zhang, 2007; Alpa Arora, 2010). Children are more compliant and conform to the regulations drawn up by their parents. As a result, children who come from Asia, they have high self-discipline in addition to having high respect for older people. This situation formed, children who are polite and always take care of the family's image in the eyes of the public (An Yun Long, 1999; Siu Man, 2002; Zhang et al., 2005; Zhang et al., 2007). A study conducted in Malaysia families in recent years found that most urban households in the country use the conversation orientation and conformity orientation equally (Aziyah, 2012; Narimah et al., 2008; Salleh Hassan et al., 2011). This shows that although parents allowed their children to carry out their activities, parents still enforce rules so that their children's behavior is under control. This is beneficial to the children as well.

Instrument of Family Communication Patterns

Instrument of family communication patterns consists of questions about conversation orientation and conformity orientation. There are 15 items to measure conversation orientation (1 - 15) and 11 items to measure conformity orientation (16 - 26). All questions in this section measured based on a 10-point Likert scale (1) Strongly disagree, to (10) Strongly agree. Among the questions relate to conversation orientation are "Parents will ask my opinion when we are discussing something" and "I enjoy talking with my parents, even if we disagree about something." Cronbach alpha values by Narimah's et al (2008) in their studies showed 0.79 on measuring conversation orientation. Meanwhile, Cronbach alpha values are 0.82 on measuring conformity orientation. The overall measure for family communication patterns in the study is 0.82. According to Zaidatul and Mohd Saleh (2003), Cronbach alpha values are between 0.6 and 1.0 which indicate a measurement instrument that is good and suitable to be used in the study.

Meanwhile, the question of the orientation of conformity consists of the following questions. "The family expects me to obey without question when it comes to important matters", "In the family, parents always have the final say on all matters" and, "Parents say children cannot speak against the parents". Cronbach alpha values for the scale orientation of conformity, in previous studies, was 0.82 (Narimah et al., 2008). While the study is 0.76. Although the alpha value differs from earlier studies, this is considered good and suitable as the Cronbach alpha values are more than 0.6 (Zaidatul & Mohd Salleh, 2003).

METHODOLOGY

Sample size requirement

This study used quantitative methods by collecting data through questionnaires. In the first place, this study adopted the traditional Cronbach Alpha resulting from the pilot survey. This value will then be confirmed by the Confirmatory Factor Analysis (CFA). As such techniques are before evaluating the measurement model since the nature of this paper was centered on theory testing. At the outset, the reliability of the questionnaire measured using the traditional Cronbach Alpha as always being treated in many publications insofar. Because the Cronbach Alpha was able to discover which item corresponding to the related study. For this reason, the Cronbach Alpha was quantified when the researchers deal with the pilot survey and then the questionnaire was re-structured with the existence of items that have high reliability. The items that have high reliability will have a high chance to assess the construct properly and the high chance to derive meaningful conclusions.

Nevertheless, the proper minimum sample size was another important issue in statistical inferential as the sample size must reflect the intention of the actual population. This is because the result which based on the sample drawn should be generalized to the true population and therefore the statistical power test is always mentioned in empirical science. Accordingly, the population of the study was about of 21,029 among high school students from three states which are Kelantan, Terengganu, and Pahang (eastern region) which means the stratified sampling was embraced. Using Krenjcie & Morgan table, the minimum sample size was about 384. This is for the population size of 1,000,000 whereas Cohen's results suggest 400. Thus, 800 questionnaires were printed and then disseminated to the respondent targeted.

Afterward, the data distributions were identified through Kolmogoror and Mahalanobis which indicate the distribution of the data available. The results found that the data was suited for the parametric technique as the bell-shaped distribution occurred. As the main focus of the study is to compare the performance of the conventional SEM and modern PLS when dealing with the second-order construct, the nature of these two statistical methodologies are discussed.

The Second Order Construct

In this paper, the use of a second-order construct was used to represent the Family Communication Pattern Model. This is the only paper that offers the comparison of conventional SEM and Modern PLS on the second-order construct for family research. The second-order construct can be regarded as one of the higher-order component model (Asnawi et al., 2019) that is best developed based on several sub-constructs or components. It can be meaningful when the researchers are aware that the dimensions should be posited under the same latent variable. In SEM, two known models are first-order and second-order constructs. The first order construct displayed several items that are necessary to measure the latent variable. Second-order construct displayed several first-order constructs with their corresponding items to measure the latent variable. The study on second-order construct was frequently applied with conventional SEM but none for modern PLS. As a consequence, more researchers believe conventional SEM is more effective than modern PLS when a particular problem cannot be captured by a single perspective (second-order construct).

For the example of a second-order construct, Parasuraman (1985) disclosed that the service quality consists of 5 dimensions that are responsiveness, tangible, reliability, empathy, and assurance. All of these dimensions are combined to form the service quality variable. In that case, one can be concluded that service quality is the second-order and the dimensions are regarded as the first order construct. Using this strategy, we figure out the Family Communication Pattern Model can be adopted for the second-order construct. Because the Family Communication Pattern Model is formed by the inclusion of two sub-constructs that are Conversation Orientation and Conformity Orientation. Every sub-construct has its respective items that are developed based on the literature theories. In this case, we have 26 items to measure the Family Communication Pattern Model (Conversation Orientation = 15 items, Conformity Orientation = 11 items). Apart from that, the second-order construct can be fully regarded as Higher-Order Component Model (HOCM).

The nature of PLS-PM

Starting with the initial work of Herman Wold (1973), there is another branch of the Partial Least Square (PLS) method which was developed for operating the multiple variables simultaneously that was called Partial Least Square Path Modeling (PLS-PM). Herman proposed Structural Equation Modeling (SEM) based on PLS as an alternative to Joreskog method (Conventional SEM). The PLS-PM estimates the parameters using the system of structural equation model which integrated with the PLS method, which avoids restriction on the distribution of the data and large sample size (Morales, 2011). Herman Wold did not agree with the seminal work of Joreskog published in Structural Equation Models in the social science in early of 1970.

It was because Joreskog approach imposed strong hypotheses and assumptions on data distribution and required a high number of cases or large sample sizes under the multivariate method. For this reason, most of the researchers unable to utilize the conventional SEM as the sample size required was high. To prevent such strong assumptions within the system of structural equation models, the PLS-PM relaxes the assumption that holds across the covariation between a block of indicators which means the indicators will be explained by the existence of common factor (Henseler, Hubona, & Ray, 2016). Therefore, the covariance and correlation between variables are not necessary to be visualized in the model for minimizing the measurement error. Furthermore, the sample size requirement for PLS-PM does not entail high samples as the result produced are remain impenetrable with the presence of high statistical power (high potential to reject the null hypothesis). According to Chin (1999), the PLS-PM was able to execute the path analysis with samples of 20.

Traditionally, PLS-PM is formally attributed by two sets of linear equations that are the measurement model and the structural model. The measurement model specifies the relationships between the latent variable and observes variables whereas the structural model specifies the relationships between the latent variables. Compared to conventional SEM, the measurement model cannot be drawn isolated. Additionally, the PLS-PM can handle the violation of distributions data, composites models for construct measurement, estimate recursive (non-feedback loops) and non-recursive structural models, conduct test of model fit, agent-based modeling, segmentation trees, higher-order model, formative construct, and multi-group analysis (Hair et al., 2014; Aziz et al., 2019). For these applications, there are several renowned statistical packages such as SmartPLS 2.0, Warp PLS, PLS Graph, PLS Gui, Spad PLS, Visual PLS, LVPLS, and XLSTAT-PLS.

The nature of Modern Partial Least Square

After a few decades, PLS-PM has undergone a series of examinations and modifications for extended the ability of PLS-PM under the structural equation modeling. Dijkstra & Henseler, (2015) proposed a new development of PLS-PM that can handle both factor models and composite models for construct measurements. It means that the belief of the nature of PLS-PM as the exploratory method was not hinder themselves to be effective as well for the confirmatory method. According to Evermann & Tate (2016), conventional structural equation modeling was the rationale for theory testing or theory-driven. As such, the confirmatory method always being interpreted for those interested in structural equation modeling for the testing theory for confirmation or justification of conclusions. It was modified as the researchers lately do not know how to distinguish between those of the exploratory and confirmatory approach and in turn, the result of coefficients leads to the improper solutions of hypotheses testing.

With the new impressive development of PLS-PM, the uncertainty to distinguish between the factor model and composite model with SEM can be solved. It was called consistent PLS (PLSc) or modern PLS where it can correct the bias coefficients. The simulation studies based Dijkstra & Henseler (2015a) and Dijkstra & Henseler (2015b) affirmed the ability and potential of this new method of determining the relationships between latent variables as represents to the conceptual framework. Based on their findings, the path coefficients produced within the system of the structural model are being consistent and lack of bias through the Monte Carlo simulations. Additionally, the factor correlation between the latent variable can be adjusted properly that free from overestimating or underestimating the factor correlations.

Technically, the modern PLS was developed based on the true nature of PLS-PM which is the use of the ordinary least square estimator remained for running the equations that involve two steps sequentially. The parameter estimates with PLS-PM would always upward bias because the PLS estimates and loadings are only consistent at large (Wold, 1982). Consistent at large implying that a large number of sample size and great size of the model (latent variables and manifest variables) are necessary to ensure the parameter estimates and loadings are consistent. The consistent estimation would allow the different analysts to reach the same conclusions of the hypothesized model. Therefore, the founder invented one of the new reliability coefficients and then it was implanted in the conjunction of the latent variable correlations. According to Gefen et al., (2011), the parameter estimates and indicator loadings can be improved to be consistent if the analyst modified the equation of the latent variable correlations.

However, the development of this application is not fully complete (Dijkstra & Schemerlleh-Engel, 2014) and still needs more investigation by assessing the more complex relationship between latent variables. To date, the assessment for modern PLS does not test for these high relationships. As such, the sample was drawn from the actual population for identifying the main issue that remains unresolved. The new method of PLS-PM called consistent PLS (PLSc) or modern PLS where now available at certain statistical packages such as SmartPLS 3.0, WarpPLS 5.0 and Adanco 1.0.

The nature of Conventional SEM

The conventional SEM was invented by Joreskog in 1970 to estimate the parameter coefficients of the structural model using an empirical variance-covariance matrix which means the distance between predicted and actual estimation was determined. Fundamentally, the normal theory as a maximum likelihood estimator always becomes the method of choice for testing the hypothesized model. Under conventional SEM perspectives, this type of SEM can handle the common factor of construct measurement that entails strong assumptions for receive wherever data sets properties. For this reason, the conventional SEM can be recognized as 'hard modeling' that is more stringent assumptions than the PLS-PM. The stringent assumptions are necessary to make sure the model conveyed for confirming theory fits with the data sets (McIntosh et al., 2014). Moreover, the conventional SEM does hold across the covariation and correlation matrix simultaneously that emanating them becomes one of the hard multivariate approaches.

In behavioral research, the factor model hypothesized that the variances of a set of indicators can be perfectly explained by the existence of latent variable and measurement error. As concerned in many previous publications, conventional SEM entails a minimum sample size of 100 to ensure the estimation produced are accurately proper solutions and converged (Hoyle, 1995; Hair et al., 2009). Moreover, the researchers are advised to comply with all the properties of statistical assumptions as to the number of indicators per construct, probability sampling, interval or ratio scale, and equal variance. Because conventional SEM was not developed for non-parametric technique (Aimran et al., 2017). As one of the confirmatory approach, the common factor needs at least 2 or 4 indicators per construct to ensure the information obtained are sufficient for justification of conclusions (Marsh, 1987). Therefore, the single indicator of a latent variable with conventional SEM not be allowed for the analysis. It can be worthy when the single indicator considers as an observed variable.

The application of Conventional SEM becomes a common practice for testing the model-based theory that appropriates under various circumstances of fields. Although the ingredient for preparing of SEM model with conventional SEM is tougher than the modern PLS, the issue of this application in terms of their algorithm is less controversial than those of modern PLS. The reason of that is because the algorithm of conventional SEM is working when the model is identified under over-identification test which means any potential advantages that might be obtained by specifying an SEM model is able being captured (Antonakis et al., 2010; McDonald, 1996; Ronkko & Evermann, 2013). Also, an over-identification test can be used to rule out the endogeneity problem that has the potential to provide a cause of inconsistent estimates (Bollen, 1989). This means that, the standard error based conventional SEM is consistently produced when the model is identified (Marsh, 1995). Compared to PLS-PM, the standard error is produced based on the implementation of the bootstrapping technique that is being adopted to replicate data many times to ensure the standard error are converged with the data observed.

Like PLS-PM, conventional SEM can be defined by two linear equations; the measurement model and structural model. The measurement model for conventional SEM can be handle independently as the identification issue of SEM can be resolved with the existence of a parameter of regression weight. Therefore, conventional SEM was appropriate for evaluating the latent variable with their respective variables. The abundance of global fit or model fits is served for examining the degree to which the model fits the data (McIntosh et al., 2014). Typically, conventional SEM was efficient and convenient for reflective construct and this model needs at least four variables per construct if testing the individual of the measurement model. To date, there have a lot of statistical packages available for conventional SEM such as AMOS, LISREL, EQS, OpenMX, Lavaan, and Sepath.

Validity and Reliability Analysis Instruments for the pilot survey

Reliability is a measure of the ability of an instrument to measure the variables of research in the study consistently every time it is used at different times and places (Haye, 2000). Test methods and test-retest is a method used to determine the coefficient of reliability of a measurement instrument. With this method, the instrument will be evaluated repeatedly to set the same sample but at different times (Haye, 2000).

The reliability analysis used is based on the Cronbach's alpha measure of internal consistency instrument. Cronbach alpha was designed by Cronbach (1990) is a scale to measure a wide range of items (multiple-point scale). Due to family communication patterns are characteristic multiple-point scale, so this study using Cronbach alpha procedure. Cronbach alpha coefficient values between 0.6 and 1.0 indicate that a measurement instrument that is good and suitable for use in a study (Zaidatul & Mohd Salleh, 2003).

The results show the reliability coefficient for the variables studied were high, and good because its value is in the range between 0.70 and 0.80. In particular, the conversation and conformity orientation was 0.78 and 0.77.

FINDING FOR FIELD STUDY

The purpose of this study is to compare the performance of construct measurement between conventional SEM and Modern PLS. As aforementioned, both of these models were believed to tend to assess the common factor model that can quantify the latent variable model that linked to the true theories (McDonald, 1999). In such things, the model was developed in the same manner as the higher-order model consists of a second-order construct and first-order construct. The second-order construct must have at least one of the single-headed arrow pointing to the respective latent variable that embedded with their respective manifest variables (items). It was purported that the first-order construct represents one of the small elements to form the second-order construct. The technical model of higher-order constructs can be admissible when the second-order constructs pointing at least two of the first-order construct as depicted in Figure 1. If the study interest is more on confirmatory purpose, then, conventional SEM or modern PLS was the first choice in empirical research. Whenever the model was linked to the strong theories and the path relationships were determined, this type of model is preferable to opt to use the common factor models.

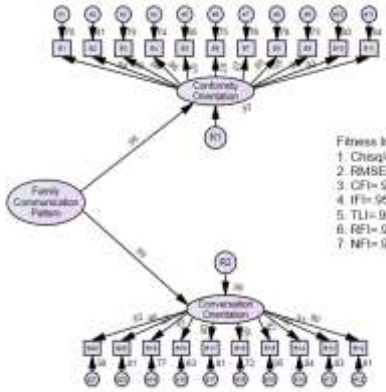
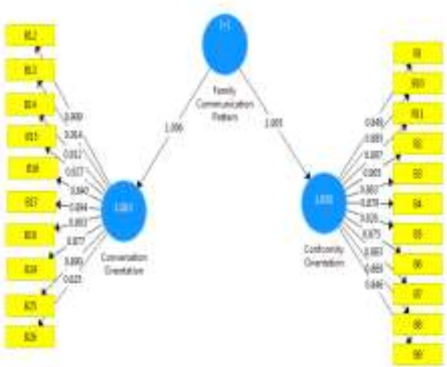
Conventional SEM	Modern PLS
	

Fig.1: Conventional SEM and Modern PLS model

The procedure to specify the model between conventional SEM and modern PLS was different as modern PLS does not necessary for the regression weight of the causal effect from second-order construct to the first-order construct. In SEM, identification has always been an important issue as the equations only work when the causal path was identified. Yet, it has been neglected in the realm of PLS path modeling since it was developed in early 1980. In other words, it is not possible to derive the statistical inferential from an unidentified model. As such, PLS fixes the variance of factor and composite to "1" to overcome the identification issue (Henseler, Hubona, & Ray, 2016). Furthermore, the measurement model of modern PLS may appear less clear than those of conventional SEM as the model usually tied with the structural disturbance, measurement error, and correlation that is must be drawn in the model. Modern PLS does not have such a requirement to derive the value of correlation and measurement error. Because PLS path modeling does not permit either constraint these parameters nor free the correlation of structural model. Additionally, it was the reason why the measurement model for modern PLS cannot measure independently (McDonald & Ho, 2002) as the constraint in PLS was not relying on the causal effects. Therefore, PLS always required at least one indicator exist in the model. Compared to conventional SEM, the model without an indicator or so-called Phantom Model (Rindskopf, 1984) can be quantified independently.

In the common practice, PLS path modeling can be fully regarded as component-based modeling that is the linear combination of respective variables that are necessary to create proxies and then use proxies to determine the parameter estimates of the structural model (Henseler, Hubona & Ray, 2016). Bentler & Huang (2014) put forth that the component model always inherits the measurement error that constitutes within that variables and in turn, it will undermine the factor correlation between latent variables (Dijkstra & Henseler, 2015). Furthers the modern PLS advent to stabilize the latent variable correlations although it seems to quickly declare such method comparable with conventional SEM. For this study, the utilization of a second-order construct may obvious harm with the identification issue. Thus, this analysis using the repeated indicator approach embedded in the main construct as it can be useful for ensuring this model can be executed.

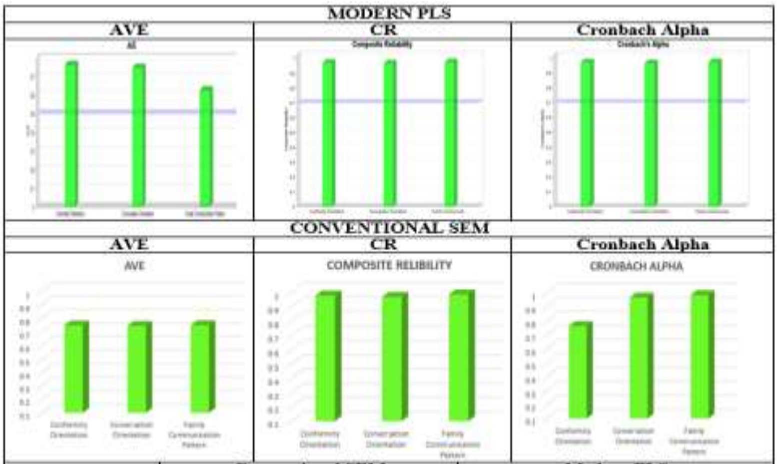
Turning back to the discussion on Figure 1, the indicators in the model represented the variables that can be derived from the data available. In behavioral research, the use of questionnaires is always frequently adopted to measure the respondents agree, opinion, perception, satisfaction, and attitudes that rely on prominent psychometric scale as Likert scale. The Likert scale may be assessed of 5 points, 7 points, or 10 points dependent on the degree of measurement scale. It was believed the 10 points of Likert scale is may the best choice of measurement scale as it is less sensitive to represent the actual intention of respondents (Hair et al., 2014; Zainudin, Afthanorhan et al., 2018) and it is should be permanently not allowed to label for each scale. Because labeling terms are the same thing to rank the scale used and it is indeed not appropriate for whatever technique that espousal of parametric assumption. In conventional SEM, measurement error for every single of variables must be drawn in the model, meanwhile, such procedure is not allowed for modern PLS. The conventional SEM will ensure the factor loadings of variables are not affected by the existence of measurement error. Thereby, the measurement error was segregate from every variable to assure the value of factor loadings are detailed.

For conventional SEM, the values of factor loadings and square multiple correlations can appear once the maximum likelihood estimator executed. Indeed, there are more other estimators as generalized least square, weighted least square, asymptotic distribution-free and unweighted least square were competent to yield such outcome. Yet, the maximum likelihood estimator was prominent as it was declared as the most convenient practice in behavioral research (Hwang et al., 2010). The measurement model of conventional SEM can be recognized valid when the model complies all the fitness index requirement such as chi-square normalized of the degree of freedom (chisq/df), Root Mean Square Error Approximation (RMSEA), Comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker Lewis Index (TLI) or Non-normed Fit Index (NNFI), Relative Fit Index (RFI) and Normed Fit Index (NFI) as demonstrated at Figure 1. The value of each fit index was beyond the threshold stipulated by the founder. The foundation of every fit was actually to determine the fitness of the model that is tested and to answer the research question of the study whether the model proposed appropriate or inappropriate to test the path relationships between them. Such a requirement would be able to convince the researcher to begin their analysis until it was completely done for answering every research questions and research hypotheses. The results of fitness index of this study were satisfied as Chisq/df = 1.695 < 3.0 (Bentler, 1990; Wheaton et al., 1977; Carmines & Mciver, 1981; Marsh & Hocevar, 1985; Byrne, 1989; Afthanorhan et al., 2019), RMSEA = 0.052 < 0.08 (Browne & Cudeck, 1993; Al-Mhasnah et al., 2018, CFI = 0.954 > 0.90 (Bentler, 1990), IFI = 0.954 > 0.90 (Bollen, 1989), TLI = 0.938 > 0.90 (Bollen, 1989; Bentler & Bonett, 1980), RFI = 0.924 > 0.90 (Bollen, 1986), and NFI = 0.942 > 0.90 (Bentler & Bonett, 1980).

For modern PLS, the value of factor loadings or outer loading and coefficient of determination can appear when it relates to the PLS algorithm that integrates with the ordinary least square estimator (McIntosh et al., 2014). To date, the ordinary least square estimator is the only one estimator exist in the application of PLS although there are more recent literature proposes another estimator for improvement. The measurement model for modern PLS is more implicit than conventional SEM as the structural disturbance and measurement error are not necessary to be visualized in the model. Therefore, the model implies that the latent variable of modern PLS is more relaxed.

Because the estimator adapted hinders the ability of PLS path modeling to derive the fitness model. The fitness index will explain the distance between the actual and predicted estimation. The small distance between them shows the predicted estimation is more precise and in turn, the model will be declared fit. Nevertheless, modern PLS needs two steps estimations to obtain the value for each latent variable and component weight for each block indicators (Hwang, Takane & Tenenhaus, 2015) that is the main reason why PLS suffered from the absence of fitness index. Logically, the fitness index can be used when the model involves a single optimization criterion (first step estimation) that cannot be dealt with PLS application since its inception. Recent literature of PLS application specified that the model fit can be assessed through Standardized Residual Mean Root (SRMR) although it is still lag far behind the conventional SEM. With this, the study just presents one model fit as SRMR = 0.068 < 0.08 (Henseler, Hubona, & Ray, 2016) indicating that the model-based modern PLS was satisfied.

Both of these applications were seemed consented to declare the model involved was fit and appropriate being tested under the common factor analytics. Additionally, the value of factor loading appear in the model of conventional SEM was high that is in the range between 0.62 to 0.92, meanwhile, modern PLS also promising to carry high factor loading when the results show from 0.625 to 0.927. At the beginning of the research, the model has 26 variables that need to be validated by conventional SEM, and modern PLS. During statistical testing, both application conventional SEM and modern PLS have removed 5 variables (B20, B21, B22, B23, and B24) that seemed to fail to regress of indicators to the corresponding with their latent variables due to low indicator loadings. Ultimately, the remaining variables of the model are considered for the reliability and validity as depicted in Figure 2. The whole latent variable in the model must be identified with its reliability and validity through Composite Reliability (CR), Cronbach Alpha, Average Variance Extracted (AVE) and Discriminant validity. Each assessment of reliability and validity model were measured directly based on the factor loading of variables remained in the model.



Constructs	Conventional SEM AVE	Conventional SEM Composite Reliability	Conventional SEM Cronbach Alpha	Modern PLS AVE	Modern PLS Composite Reliability	Modern PLS Cronbach Alpha
Conformity Orientation	0.748	0.976	0.761	0.762	0.972	0.972
Conversation Orientation	0.745	0.966	0.965	0.745	0.967	0.966
Family Communication Pattern	0.749	0.984	0.983	0.625	0.976	0.973

Figure 2: Comparing reliability and validity between conventional SEM and modern PLS

Fig.2:

The result of the reliability and validity of construct measurement was centered in Figure 2. In SEM, the requirement of AVE, CR, and Cronbach Alpha is necessary as one of the complementary fashion for examining the magnitudes of the estimated parameters in the model. Nevertheless, the model must be fit in the first place as it represents how well the model fits the sample data (McIntosh et al., 2014) that is the model fit was examined. Generally, model fit provides summaries of how well the model structures in terms of the number of latent variables, manifest variables, and constrained parameter (correlation among the observed variables). Thereby, the remaining variables in the model must carry high factor loading as it is part of AVE and CR for ensuring the model was conclusive. Strictly speaking, the acceptable of factor loadings for SEM was higher than 0.60 such that it can provide great help for enhancing the value of AVE and CR.

Fornell & Larcker (1981) contend that convergent validity (i.e: AVE) was acknowledged when the value is higher than 0.50. Other than that, the model claimed to fail to achieve their validity and cannot be further estimated of testing the hypothesized relationships among latent variables. It means that the model replete with the existence of error that may overestimate or underestimate the path coefficient of the structural model and consequently have a tendency to condense the statistical power estimation. For this reason, the model must capture more than 50%

or 0.50 of the total variance (square root of standard error) of the measurement model to free the model from tremendous error in the model.

Furthers the reliability of the model was measured through CR as always being treated wherever of behavioral research. CR was declared contented when the value obtained is higher than 0.70 (Nunally & Bernstein, 1994). It was alleged more significant than the traditional reliability as Cronbach Alpha when it involves of the second-generation method (Zainudin, 2015). Because CR takes into account the measurement effect rather than the Cronbach Alpha that much more assuming on every single of indictor effects. The value of Cronbach Alpha was a customary rationale with an outcome higher than 0.70.

In this study, all requirements for testing the reliability and validity were satisfied as unveiled in Figure 2. To bolster the clarification of construct reliability and validity, the measurement model was compared and contrasted to ensure the discovery will be more informative. Under conventional SEM perspectives, the latent variable of conformity orientation was appeared more reliable and valid compared to other sub-constructs namely conversation orientation. Like conventional SEM, the modern PLS concurred to claim conformity orientation was seemed more valid and reliable. Among those applications utilized, conventional SEM was seemed more pronounced than those of modern PLS when the Family Communication Pattern as a second-order construct was acknowledge maintained the reliability and validity respectively.

CONCLUSION

The point of departure in this paper is to compare the performance of conventional SEM and modern PLS when the second-order construct was measured directly by using a common factor model, which means the model being tested was concerned under the confirmatory sense. The utmost information of this comparison between both of that application is conveyed solely by the existence of one unobserved variable of the main construct with their respective unobserved variable of sub-constructs.

In common practice, one may deal with conceptually flawless situations when it involves statistical power test, loading matrices, correlation, and covariance matrices, standard error, vary of data properties, the convergence of estimations, and model structures that are more complicated than one handled in this paper. How effective of modern PLS when relates to common factor is remained unclear, but it is still can be great and helpful for those intend to concentrate on the composite factor. These topics include the second-order model structure (Family Communication Pattern) and then compare with their reliability and validity as part of the important issue when one's interest to validate their measurement model.

From the findings appear in this paper, the modern PLS seemed powerful as conventional SEM which makes modern PLS suitable for confirmatory research. The measurement model between those applications was provided the same model structure as both of them concurred to delete 5 variables from those models. Plus, the variables removed from those models quite similar. However, there is some issue present in the measurement model for modern PLS when it involves of common factor method. For these reasons, the model for modern PLS was possibly faced with the presence of Heywood cases when the value of the causal effect from second-order to the first-order construct that greater than 1.0. In contrast, the conventional SEM was not faced with such an issue although it was declared a common factor method. One can be concluded that the chance possibility of modern PLS towards Heywood cases was high. Therefore, we agree with Henseler, Hubona & Ray (2015) exposition when the modern PLS may have Heywood issue when involving a common factor. It might be happening because the presence of consistent PLS is still fresh to be tested in the higher model. So, it is not fair for us to condemn the consistent PLS and placing the conventional SEM as the method of choice when the holds the common factor. Nevertheless, modern PLS may appropriate for a model that relates to the first-order construct under confirmatory sense. A serious examination and investigation into the extent to which the exposition is valid will be a major experiment for second-order construct. Because the requirement of the second-order construct in empirical research lately becomes one of the favorable approaches in providing much more information on the related studies. Additionally, future research may include more complex relationships between latent variables such that to provide evidence that the development of modern PLS can accommodate both construct measurement of the composite method and common factor method. Furthermore, we anticipate that modern PLS might be superior to conventional SEM to compensate for the complex relationships between composite variables.

REFERENCES

1. 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.
2. Afthanorhan, A., Awang, Z., Rashid, N., Foziah, H., & Ghazali, P. (2019). Assessing the effects of service quality on customer satisfaction. Management Science Letters, 9(1), 13-24.
3. 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.
4. AL-Mhasnah, A., Salleh, F., Afthanorhan, A., & Ghazali, P. (2018). The relationship between services

quality and customer satisfaction among Jordanian healthcare sector. Management Science Letters, 8(12), 1413-1420.
5. Asnawi, A., Awang, Z., Afthanorhan, A., Mohamad, M., & Karim, F. (2019). The influence of hospital image and service quality on patients' satisfaction and loyalty. Management Science Letters, 9(6), 911-920.
6. Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On making causal claims: A review and recommendations. The Leadership Quarterly,21(6), 1086-1120.
7. Aziz, M., Adnan, A., Afthanorhan, A., Foziah, H., Ishak, S., & Rashid, N. (2019). The influence of employer value proposition in talent demand towards talent shortage in the Malaysian Islamic banking institutions: A SEM approach. Management Science Letters, 9(6), 843-850.
8. Allison, B.A. (2000). Parent-adolesent conflict in early adolescence: Research and implication for middle school programs. Journal of Family and Consumer Sciences Education, 18 (2).
9. Alpa Arora, B. (2008). Family dynamics & communication patterns in India-American families: Perspectives of second-generation young adults. Unpublished doctoral dissertation, Alliant International University. Available from: Disertation & Theses: Full Text (Publication No. ADT 3331906). Access at November 6, 2010.
10. Ballard-Reisch, D. S., & Weigal, D.J. (2006). Established and promising models for family communication research. Reno: University of Nevada.
11. Baxter, L.A., Bylund, C.L., Imes, R.S., & Scheive, D. M. (2005). Family communication environments and rule-based social control of adolescents' healthy lifestyle choices. Journal of Family Communication, 5(3), 209-227.
12. Braithwaite, D. O., McBride, M. C., & Schrodt, P. (2003). "Parent teams" and the everyday interactions of co-parenting in stepfamilies. Communication Reports. 16(2): 93-111.
13. Bentler, P. M. (1990). Comparative fit indexes in structural models. Psychological bulletin, 107(2), 238.
14. Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. Psychological bulletin, 88(3), 588.
15. Bentler, P. M., & Huang, W. (2014). On components, latent variables, PLS and simple methods: Reactions to Rigdon's rethinking of PLS. Long range planning, 47(3), 138-145.
16. Bollen, K. A. (1986). Sample size and Bentler and Bonett's onnormed fit index. Psychometrika, 51(3), 375-377.
17. Bollen, K. A. (1989). A new incremental fit index for general structural equation models. Sociological Methods & Research, 17(3), 303-316.
18. Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. Sage focus editions, 154, 136-136.
19. Byrne, B. M. (1989). Multigroup comparisons and the assumption of equivalent construct validity across groups: Methodological and substantive issues. Multivariate Behavioral Research, 24(4), 503-523.
20. Carmines, E. G., & McIver, J. P. (1981). Analyzing models with unobserved variables: Analysis of covariance structures. Social measurement: Current issues, 65-115.
21. Cronbach, L.J. (1990). Essentials of psychological testing (5th ed.). New York: Harper & Row.
22. Dumlao, R., & Botta, R.A. (2000). Family communication patterns and the conflict styles young adults use with their fathers. Communication Quarterly, 48, 174-189.
23. Dijkstra, T. K., & Henseler, J. (2015a). Consistent and asymptotically normal PLS estimators for linear structural equations. Computational statistics & data analysis, 81, 10-23.
24. Dijkstra, T. K., & Henseler, J. (2015b). Consistent partial least squares path modeling. MIS quarterly= Management information systems quarterly, 39(2), 297-316.
25. Evermann, J., & Tate, M. (2016). Assessing the predictive performance of structural equation model estimators (Forthcoming).
26. Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. Journal of marketing research, 382-388.
27. Fitzpatrick, M. A., & Ritchie, L. D. (1994). Communication Schemata within the family; multiple perspectives on family interaction. Human Communication Research. 20: 275-301.
28. Gefen, D., Straub, D. W., & Rigdon, E. E. (2011). An update and extension to SEM guidelines for admnistrative and social science research. Management Information Systems Quarterly, 35(2), iii-xiv.
29. Hair Jr, J. F., Gabriel, M. L. D. D. S., & Patel, V. K. (2014). Amos Covariance-Based Structural Equation Modeling (Cb-Sem): Guidelines on its Application as a Marketing Research Tool.
30. Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). Análise multivariada de dados. Bookman Editora.
31. Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. Industrial Management & Data Systems, 116(1), 2-20.
32. Hayes. (2000). Doing psychology research. Philedelphia: Open University Press.
33. Hoyle, R. H. (Ed.). (1995). Structural equation modeling: Concepts, issues, and applications. Sage

Publications.
34. Hwang, H., Malhotra, N. K., Kim, Y., Tomiuk, M. A., & Hong, S. (2010). A comparative study on parameter recovery of three approaches to structural equation modeling. Journal of Marketing Research, 47(4), 699-712.
35. Hwang, H., Takane, Y., & Tenenhaus, A. (2015). An Alternative Estimation Procedure for Partial Least Squares Path Modeling. Behaviormetrika, 42(1), 63-78.
36. Jusang Bolong. (2006). Virtual community and social cohesion relationship through computer-mediated interpersonal communication. Ph.D thesis unpublished, Serdang: University of Putra Malaysia.
37. Kelley, L., Keaten, J.A., Finch, C., Duarte, I. B., Hoffman, P., & Michels, M.M.(2002). Family communication patterns and the development of reticence. Communication Education, 51(2), 202-209.
38. Koerner, A. F., & Fitzpatrick, M.A. (2004). Communication in intact families. In A Vangelisti (Ed,), Handbook of family communication (pp. 177-196). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
39. Koestan, J. (2004). Family communication patterns, sex of object, and communication competence. Communication Monographs, 71, 226-244.
40. Marsh, H. W. (1987). Students' evaluations of university teaching: Research findings, methodological issues, and directions for future research. International journal of educational research, 11(3), 253-388.
41. McDonald, R. P. (1996). Path analysis with composite variables. Multivariate Behavioral Research, 31(2), 239-270.
42. Marsh, H. W., & Hocevar, D. (1985). Application of confirmatory factor analysis to the study of self-concept: First-and higher order factor models and their invariance across groups. Psychological bulletin, 97(3), 562.
43. Mateos-Aparicio, G. (2011). Partial least squares (PLS) methods: Origins, evolution, and application to social sciences. Communications in Statistics-Theory and Methods, 40(13), 2305-2317.
44. McDonald, R. P., & Ho, M. H. R. (2002). Principles and practice in reporting structural equation analyses. Psychological methods, 7(1), 64.
45. McIntosh, C. N., Edwards, J. R., & Antonakis, J. (2014). Reflections on partial least squares path modeling. Organizational Research Methods, 1094428114529165.
46. Narimah Ismail, Siti Zobidah Omar, Jusang Bolong, Musa Abu Hassan, Saodah Wok, Haniff Hassan & Aziyah Abu Bakar. (2008). Family communication practices among farmers. Papers presented at the seminar, Communication and Computer Use in the Family Farmers, in Malaysia. Serdang, University of Putra Malaysia, November 27.
47. Nunally, J. C., & Bernstein, I. H. (1994). Psychonometric theory. New York.
48. Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. Journal of Marketing, 41-50.
49. Rindskopf, D. (1984). Using phantom and imaginary latent variables to parameterize constraints in linear structural models. Psychometrika, 49(1), 37-47.
50. Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. Organizational Research Methods, 1094428112474693.
51. Siu Man, H.A. (2002). Interpersonal competence, family functioning, and parent-adolescent conflicts. Unpublished doctoral dissertation, The Chinese University of Hong Kong. Available from: Dissertation & Theses: Full Text (Publication No. ADT 3331906). Access at November 6, 2010.
52. Trubisky, P., Ting-Toomey, S., & Lin, S.L. (1991). The influence of individualism-collectivism and self-monitoring on conflict styles. International Journal of Intercultural Relations, 15, 65-84.
53. Wilson, S.R., & Morgan, W.M. (2004). Persuasion and families. In A. Vangelisti (Ed.), Handbook of family communication (p:447). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
54. Wood, J.T.(2004). Interpersonal communication: Everyday encounters. Belmont, CA:Thomson Wadsworth.
55. Wheaton, B., Muthen, B., Alwin, D. F., & Summers, G. F. (1977). Assessing reliability and stability in panel models. Sociological methodology, 8(1), 84-136.
56. Wold, H. (1973). Nonlinear iterative partial least squares (NIPLAS) modelling: Some current developments. Univ., Department of Statistics.
57. Wold, H. (1982). Soft modelling: the basic design and some extensions. Systems under indirect observation, Part II, 36-37.
58. Zaidatul Tasir & Mohd Salleh Abu. (2003). Analisis data berkomputer SPSS 11.5 for windows. Kuala Lumpur: Venton Publishing (M) Sdn. Bhd.
59. Zhang, Q. (2007). Family communication patterns and conflict style in Chinese parent-child relationships. Communication Quarterly, 55, 113-128.
60. Zhang, Y.B., Harwood, J., & Hummert, M.L. (2005). Perceptions of conflict management styles in Chinese intergenerational dyads. Communication Monographs, 72, 71-91.
61. Zainol, R, N., Zainol., A., F., Ibrahim, Y., Afthanorhan, A. (2019). Scaling up social innovation for sustainability: The roles of social enterprise capabilities. Management Sciences Letters, 9(3), 1-10.