Chapter 7
An Introduction to a Permutation Based Procedure for Multi-Group PLS Analysis: Results of Tests of Differences on Simulated Data and a Cross Cultural Analysis of the Sourcing of Information System Services Between Germany and the USA

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Abstract To date, multi-group comparison of Partial Least Square (PLS) models where differences in path estimates for different sampled populations have been relatively naive. Often, researchers simply examine and discuss the difference in magnitude of specific model path estimates from two or more data sets. When evaluating the significance of path differences, a t-test based on the pooled standard errors obtained via a resampling procedure such as bootstrapping from each data set is made. Yet problems can occur if the assumption of normal population or similar sample size is made. This paper provides an introduction to an alternative distribution free approach based on an approximate randomization test – where a subset of all possible data permutations between sample groups is made. The performance of this permutation procedure is tested on both simulated data and a study exploring the differences of factors that impact outsourcing between the countries of US and Germany. Furthermore, as an initial examination of the consistency of this new procedure, the outsourcing results are compared with those obtained from using covariance based SEM (AMOS 7).

7.1 Introduction

Partial Least Squares (PLS) modeling has been gaining attention among social scientists in recent years (e.g., Chin 1995; Chin and Higgins 1991; Fornell 1982; Mathieson 1991; Sambamurthy and Chin 1994). One of the reasons is that the

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PLS approach, consistent with standard structural equation modeling precepts, provides the researcher with greater ability to predict and understand the role and formation of individual constructs and their relationships among each other (Chin 1998b; Hulland 1999). Moreover, PLS is often considered more appropriate than covariance-based modeling techniques like LISREL when the emphasis is prediction since it attempts to maximize the explained variance in the dependent construct. Furthermore, sample size requirements are considerably smaller than the minimum recommended for covariance-based techniques especially for complex models (Chin and Newsted 1999). In the case of multi-group structural equation modeling (MGSEM), advanced procedures for group comparison have been implemented in covariance-based SEM (e.g., as provided in AMOS 7.0). This approach, however, can pose high demands on data properties and sample size. Another less restrictive way of testing structural equation models across groups is the use of the component-based procedure, partial least squares (PLS).

To date, multi-group comparison of PLS models where differences in path estimates for different sampled populations have been relatively naive. Often, researchers simply examine and discuss the difference in magnitude of particular model path estimates for two or more data sets (e.g., Thompson et al. 1994). When assessing the significance of the differences, a t-test based on the pooled standard errors obtained via a resampling procedure such as bootstrapping from each sample is made (e.g., Keil et al. 2000). Yet problems can occur if the assumption of normal population distribution or similar sample size is not tenable. As an alternative distribution free approach, this paper will present the results of applying an approximate randomization test – where a subset of all possible data permutations between sample groups is made. In assessing the significance for a two-sided permutation test, we could examine whether the originally observed difference falls outside of the middle $n\%$ (e.g., 95 or 99 percentile) of the distribution of differences for the subset runs performed. But typically, a one-sided test is performed to examine the percentage of subset runs that are greater than the original observed difference. The performance of this permutation procedure is tested on both simulated data and a study exploring the differences of factors that impact outsourcing between the countries of US and Germany. Furthermore, for reasons of curiosity and in order to examine the consistency of this new procedure, the outsourcing results will be compared with those obtained from using covariance based SEM (AMOS 7).

7.2 The Permutation Procedure

Randomization, or permutation procedures are now the preferred tests of significance for non-normal data. These techniques are considered distribution-free tests in that they require no parametric assumptions. Randomization tests should not be viewed as alternatives to parametric statistical tests, rather they should be considered as those tests for that particular empirical form being examined. The availability of fast computers has made permutation tests increasingly feasible, even for large data sets. Since such methods require no particular assumptions concerning statistical distributions (with the exception of the important assumption of independent observations), permutation tests are increasingly applied even in the context of traditional statistical tests (e.g. correlation, t-tests, ANOVAs, etc.).

The procedure for a permutation test based on random assignment, as described by Edgington (1987) and Good (2000), is carried out in the following manner.

1. A test statistic is computed for the data (e.g., contrasting experimental treatment/control or nonexperimental groupings).
2. The data are permuted (divided or rearranged) repeatedly in a manner consistent with the random assignment procedure. With two or more samples, all observations are combined into a single large sample before being rearranged. The test statistic is computed for each of the resulting data permutations.
3. These data permutations, including the one representing the obtained results, constitute the reference set for determining significance.
4. The proportion of data permutations in the reference set that have test statistic test statistic values greater than or equal to (or, for certain test statistics, less than or equal to) the value for the experimentally obtained results is the P-value (significance or probability value). For example, if your original test statistic is greater than 95% of the random values, then you can reject the null hypothesis at $p < 0.05$.

Determining significance on the basis of a distribution of test statistics generated by permuting the data is characteristic of all permutation tests. When the basis for permuting the data is random assignment, that permutation test is often called a randomization test. This preceding definition is broad enough to include procedures called randomization tests that depend on random sampling as well as randomization. The modern conception of a randomization test, however, is a permutation test that is based on randomization alone, where it does not matter how the sample is selected.

A permutation test based on randomization, as Edgington (1987) notes "is valid for any kind of sample, regardless of how the sample is selected." This is an extremely important property because the use of nonrandom samples is common in surveys and experimentation and would otherwise invalidate the use of parametric statistical tables (e.g., t or F tables). Essentially, the random sampling assumption underlying these significance tables states that all possible samples of n cases within a specified population has the same probability of being drawn.

Statisticians going back to Sir Ronald Fisher (1936, p. 59, c.f., Edgington 1987) have indicated that the randomization test is the correct test of significance and that the corresponding parametric test is valid only to the extent the results yield the same statistical decision. Fisher, in particular, referred to the application of permuting the data to determine significance. But Efron and Tibshirani (1993, p. 202) noted that Fisher introduced the idea of permutation testing "more as a theoretical argument supporting Student's t-test than as a useful statistical method in its own right." With modern computational power available for permutation tests to be used on a routine basis, the reliance on parametric tests as an approximation is no longer necessary.

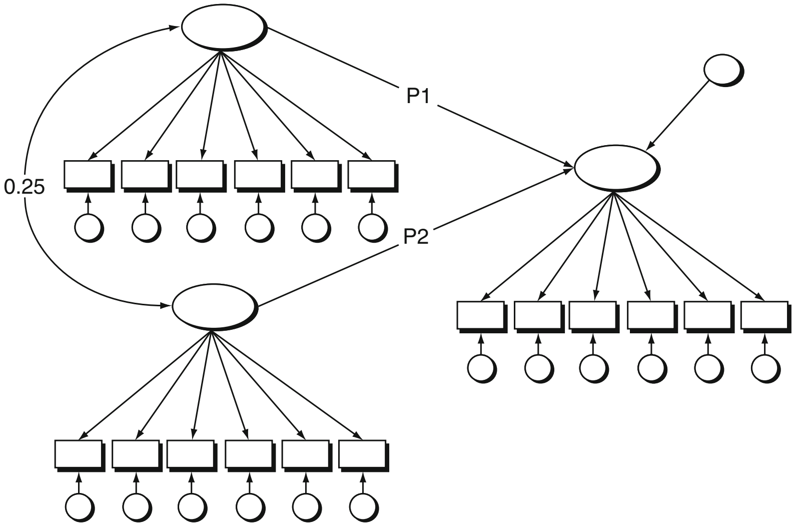

Fig. 7.1 Base model tested with structural paths $P1$ and $P2$ varied

Good (2000) clearly articulates that when samples are very large, decisions based on parametric tests like the t and F tests usually agree with decisions based on the corresponding permutation test. But with small samples, "the parametric test will be preferable IF the assumptions of the parametric test are satisfied completely" (Good 2000, p. 9). Otherwise, even for large samples, the permutation test is usually as powerful as the most powerful parametric test and may be more powerful when the test statistic does not follow the assumed distribution (Noreen 1989, pp. 32–41).

In this paper, we examine the two sample situation where two independent random samples $G1 = (m_1, m_2, \ldots, m_i)$ and $G2 = (n_1, n_2, \ldots, n_k)$ are drawn from potentially two different probability distributions D_{G1} and D_{G2}. The test statistic is the difference in the PLS parameter estimates such as $P1$ and $P2$ as seen in Fig. 7.1 (i.e., $e = P1 - P2$). Having observed sample sets G_1 and G_2, we test the null hypothesis H_0 of no difference between D_{G1} and D_{G2} (i.e., $H_0 : D_{G1} = D_{G2}$).

7.3 Monte Carlo Design

Figure 7.1 provides the basis for the Monte Carlo generated data. Two exogenous constructs, labeled X and Z, are created with a correlation of 0.25. Both are modeled to impact the endogenous construct Y. Six indicators were created as measures reflecting each construct. The standardized loadings were set at 0.6 for three indicators and 0.8 for the other three indicators. While not a full factorial design, the cells studied provides initial information to contrast varying structural path effect sizes with data normality (normal versus high kurtosis). In addition, asymmetry in

Table 7.1 Power for $p < 0.05$ significance level for path differences (percentages out of 1,000 runs)

		Path setting 1 Group 1 ($p1 = 0.5$, $p2 = .03$) Group 2 ($p1 = 0.3$, $p2 = .05$)	Path setting 2 Group 1 ($p1 = 0.7$, $p2 = .05$) Group 2 ($p1 = 0.5$, $p2 = .07$)	Path setting 3 Group 1 ($p1 = 0.6$, $p2 = .03$) Group 2 ($p1 = 0.3$, $p2 = .06$)
Data Setting 1	$N = 150$ (group 1), $N = 150$ (group 2)		82.0 ($p1$) 83.0 (p2)	90.3 ($p1$) 88.2 (p2)
Data Setting 2	$N = 150$ (group 1), $N = 75$ (group 2)		64.9 ($p1$) 68.3 ($p2$)	76.9 ($p1$) 76.5 ($p2$)
Data Setting 3	$N = 150$ (group 1) $N = 150$ (group 2) non-normal conditions	na ($p1$) 66.9 ($p2$) setting A	66.6 ($p1$) 67.0 ($p2$) setting B	78.8 ($p1$) 79.0 ($p2$) setting C

sample sizes for the two groups was also tested (150 cases for both versus 150 and 75 for groups 1 and 2 respectively). Data were generated using PreLis 2 (Jöreskog and Sörbom 1996). For non-normal data, the generalized Lambda distribution suggested by Ramberg et al. (1979) was used following the procedure described by Reinartz et al. (2002).

The structural paths were varied symmetrically with the effects for the two causal paths in group 1 the same, but reversed of group 2. Thus, for example, in the first effect treatment the standardized paths were set for $P1$ at 0.5 and $P2$ at 0.3 for the group 1 and reversed with $P1$ at 0.3 and $P2$ at 0.5 for group 2. This provided the opportunity to see the performance for two paths with the same effect size differences.

Table 7.1 presents the results for those cells analyzed. Each cell represents the results of running one million PLS analysis. This is due to the fact that 1,000 Monte Carlo sample sets were created for each cell to reflect that particular condition. Then 1,000 permutations were conducted for each sample to determine the p-value for the test statistic. The first two rows represent results using normal data, whereas the last row presents results using non-normal data. For the non-normal conditions, the item skewness ranged from 0.952 to 1.759 and kurtosis (see Table 7.2) ranged from 2.764 to 18.425.

The results in Table 7.1 provide us with an initial sense of the power for detecting structural path differences for different sample populations. As typical of power analysis, the sample and effect size was found to have an impact. For the first row, we see that the power for normal data where the population path difference is 0.2 was detected at the $p < 0.05$ level approximately 82% of the time. When the difference in path was increased to 0.3 (i.e., path setting 3), the power went up to 88 for $p2$ and 90.3 for $p1$. Conversely, the power dropped when the number of cases for the second group was lowered from 150 to 75 (i.e., data setting 2). Interestingly enough,

Table 7.2 Level of kurtosis for indicators used for the non-normal runs

	setting A		setting B		setting C	
	$g1$	$g2$	$g1$	$g2$	$g1$	$g2$
$X1$	8.286	6.176	5.705	6.412	5.356	6.176
$X2$	7.748	5.503	5.498	5.392	6.410	5.503
$X3$	7.176	8.151	4.908	5.964	6.970	8.151
$X4$	9.206	4.407	4.218	6.435	4.544	4.407
$X5$	8.144	4.295	3.842	6.830	4.205	4.295
$X6$	8.068	3.880	4.555	6.220	3.784	3.880
$Z1$	6.927	5.405	4.863	4.775	6.741	5.405
$Z2$	5.345	7.502	7.297	5.754	5.392	7.502
$Z3$	5.178	5.545	5.580	5.552	7.350	5.545
$Z4$	7.566	4.483	3.841	4.211	3.628	4.483
$Z5$	6.160	5.126	4.232	6.195	3.738	5.126
$Z6$	6.517	5.667	3.726	4.308	3.978	5.667
$Y1$	5.713	5.028	5.292	5.823	7.525	5.028
$Y2$	5.999	4.672	4.489	6.165	4.896	4.672
$Y3$	5.249	5.248	9.645	6.161	4.990	5.248
$Y4$	4.847	2.874	2.765	3.610	4.092	2.874
$Y5$	4.786	3.850	2.818	3.962	3.721	3.850
$Y6$	4.690	3.056	2.974	3.909	3.899	3.056

Table 7.3 Power at $p < 0.05$ significance level for loading differences of 0.2 (percentage out of 1,000 runs for six loadings)

0.8 vs. 0.6 (normal)	0.8 vs. 0.6 (normal)	0.8 vs. 0.6 (non normal)	0.9 vs. 0.6 (non normal)
Group 1 = 150, Group 2 = 150	Group 1 = 150, Group 2 = 75	Group 1 = 150, Group 2 = 75	Group 1 = 150, Group 2 = 75
85.0 – 90.5	76.1 – 77.4	51.2 – 52.1	89.4 – 92.3

this same drop in power can also be achieved if the data was highly non-normal (i.e., data setting 3). Finally, it seems it is not simply the effect size, but also the overall magnitude of predictiveness that may make a difference. In a separate run (not presented in the table), we kept both path differences equal at 0.3, but changed the model to represent more substantive paths (i.e., 0.7 and 0.4 versus 0.6 and 0.3). The power increased a corresponding 20%.

The power to detect standardized path loading differences of 0.2 were also examined (see Table 7.3). Overall, the power ranged from 76 to 90 in the normal data settings. Under high non-normality, the power dropped to the 50 percentile range. But when the effect size was increased to 0.3 population difference, the power dramatically improved moving into the 89.4–92.3 range.

Taken together, these results are suggestive of the countervailing impact that asymmetry in group sample sizes, degree of non-normality, difference in magnitude of path effects, and overall predictiveness of the model have upon each other. In other words, while asymmetry in group sample sizes is expected to lower the power to detect structural path differences, a more predictive model, on average, may moderate this effect. Ideally, we would like high predictive models with normal data and sample sizes of 150 or higher for each group.

7.4 Cross-Cultural Analysis of an Information Systems Outsourcing Model

We now provide a didactic example of the use of the PLS based permutation procedure in a cross cultural context. The example includes the testing of a model that explains why companies outsource the development and maintenance of software applications to external vendors. Over the past 15 years, the practice of information systems (IS) outsourcing has grown significantly. Many industry watchers have attributed this growth to the first IS outsourcing mega deal in 1989, when Kodak decided to outsource major parts of their IS infrastructure to IBM, DEC and Businessland in a 10-year, $250 million deal (Dibbern et al. 2004). However, in spite of the fact that the outsourcing market has grown globally, there are a number of obvious differences between countries. First of all, when looking at the overall amount of money that is spent for IS services, it soon becomes apparent that the U.S. is still the leading country in terms of IS outsourcing expenditures with three times more money spent on IS outsourcing than Germany (Murphy et al. 1999; OECD 2000) as an example. Second, there are significant differences between countries in terms of what IS functions are being outsourced (Apte et al. 1997; Barthelemy and Geyer 2001). This phenomenon is essentially attributed to the increasing practice of selective outsourcing. That is, rather than outsourcing their entire IS department, firms prefer to outsource part or all of particular IS functions, such as data center operations, help desk services or applications development.

Thus, the question is raised as to why such national differences do exist. Is the sourcing decision fundamentally different between countries (i.e., is it motivated or restricted by different factors?) and, if yes, why so? Most research on IS outsourcing has been conducted in a single country. Indeed the majority of research is U.S.-based and it is hard to say to what extent these findings are generalizable across countries. The few studies with a cross-national perceptive are purely descriptive (Apte et al. 1997; Barthelemy and Geyer 2001).

7.4.1 Theoretical Framework

Figure 7.2 presents a graphical representation of the theoretical model to be tested. This model suggests that the decision to outsource application services is influenced by three distinct sets of variables: efficiency variables, effectiveness variables as well as social influences and other constraints. In addition, firm size similar to other studies is included as a control variable. The discussion below elaborates upon each

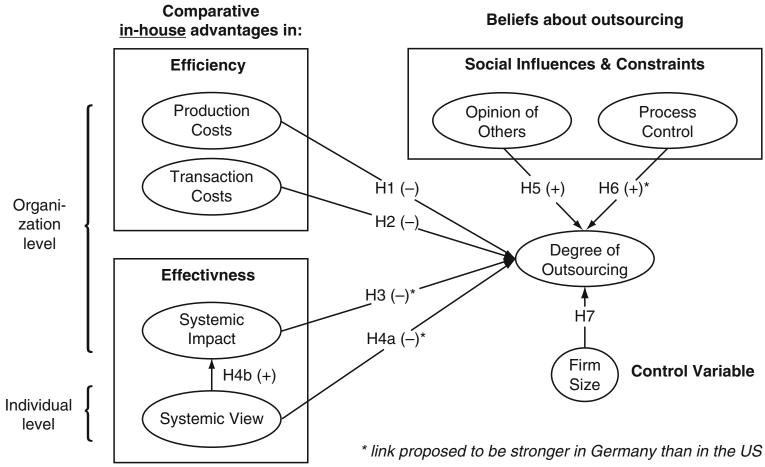

Fig. 7.2 Theoretical framework on IS sourcing

set of factors and explains why the strength of certain linkages is expected to differ between German and U.S. organizations.

7.4.2 Efficiency Factors

Production Costs. Previous empirical research on IS outsourcing has shown that cost reduction is one of the major objectives for IS outsourcing (c.f. Dibbern et al. 2004) where an external vendor can realize higher economies of scale because of its ability to provide the same type of service for multiple customers. At the same time however, it is one of the major reasons why some companies decide to keep there IS function in-house or to bring it back in-house (Dibbern et al. 2003; Hirschheim and Lacity 2000). Thus, overall, the decision of whether it is more production cost efficient to insource an IS function or to outsource it to an external vendor should be made on a case to case basis (c.f. Ang and Straub 1998).

Transaction Costs. In addition to production costs, however, transaction costs should not be neglected (Ang and Straub 1998). Transaction costs are all costs in terms of time, effort, and money spent that arise when delegating tasks of an IS function to one or more agents. The magnitude of these transaction costs may also vary between insourcing and outsourcing, and hence it is important to be clear which sourcing arrangement is more transaction cost efficient.

The argument that the make-or-buy decision should be guided by both transaction and production cost considerations can be traced back to transaction cost theory, which considered the sum of production and transaction cost differences between the firm and the market (Williamson 1981). Thus, as reflected in paths H1 and H2, the higher the comparative costs of outsourcing is relative to the firm, the less a particular application service is outsourced.

7.4.3 Effectiveness Factors

Focusing solely on *efficiency*, however, neglects the fact that the *output* of the IS work could be significantly influenced by the sourcing choice as well. Empirical findings have shown that some organizations change their current sourcing arrangement for strategic intents (DiRomualdo and Gurbaxani 1998; McLellan et al. 1995). The precondition for strategic impacts are variations in the *effectiveness* of the IS function.

Systemic Impact. For reaching a high level of IS effectiveness, it is often argued that beyond producing application software whose features and capabilities meet the needs of the users, it is even more important to ensure that an organization's application software fits synergistically with other IS functions such as data center operations, network design and maintenance, user support and telecommunications services. It is often hard to separate the effectiveness of the application software from that of the overall IS (c.f. Hamilton and Chervany 1981; Pitt et al. 1995). Accordingly, as tested via path H3, it is important for an organization to examine whether the systemic impact of application services is higher in-house or with an external vendor.

Systemic View. In line with the arguments made above and with the resource-based view (Wade and Hulland 2004), IS workers that feel responsible not only for their own work, but also for how their work relates to the work of others, may be viewed as valuable resources. IS executives, when evaluating and comparing alternative sourcing options, may well consider whether their choice leads to IS workers with more of an integrative view of the firm. This is reflected in path H4a, which suggests that the more systemic the view of in-house employees as opposed to outsourced workers in performing application services, the less these services are outsourced. Path H4b, in a similar vein, suggests that the impact of the application development and maintenance work on overall systems performance is better achieved in-house, if an organization's own employees have more of a systemic view than the personnel of an external service provider.

7.4.4 Social Influences and Constraints

Opinion of Influential Others. The preceding factors are based on the assumption that the sourcing decision represents a rational decision based on efficiency and effectiveness criteria. This view has been partially contradicted by other studies that show an organizations sourcing decision can be influenced by various social influences and constraints (Lacity and Hirschheim 1993; Lacity and Hirschheim 1995). Overall, these studies support the view that the opinion of others could have a profound impact on the sourcing decision of organizations and this is tested via path H5.

Outsourcing Process Control. A final main factor that may explain variations in the degree of outsourcing application services is extent to which organizations have control (i.e. unlimited power of direction) over all necessary activities associated with outsourcing an IS function to an external service provider. These influences may limit the ability of the main decision makers to act strictly relationally. Accordingly, one would expect that the less the implementation of an outsourcing decision is constrained by various forces, the easier it is for an organization to outsource application services. Path H6 tests for this impact. Finally, in accordance with previous studies on IS sourcing, firm size is added as a control variable and tested via path H7 (Ang and Straub 1998; Sobol and Apte 1995).

7.4.5 Proposed Cultural Differences

The preceding net of hypotheses (see Fig. 7.2) may be viewed as a mid-range theory that seeks to explain variations in the extent to which organizations outsource application services. The question for this study is whether the relationships between constructs are the same in Germany and the U.S., or whether country specific factors affect the generalizability of the proposed linkages. One way of approaching this question is (1) to identify those cultural dimensions that were found to differ between Germany and the U.S. in previous cross-cultural research, (2) to select those dimensions that have an impact on the mid-range theory, and (3) to develop propositions about how selected linkages will differ between Germany and the U.S. (based on Lytle et al. 1995).

In following this procedure, three candidates have been identified that may account for cross-cultural variation in the theoretical framework. Two of them are cross-cultural dimensions that refer to relationship characteristics between societal members, while the third refers to more general patterns of institutions and social systems (Lytle et al. 1995).

The first dimension is *individualism-collectivism* based on a large scale survey of approximately 116,000 respondents from 50 different cultural regions worldwide (Hofstede 1980). The U.S. sample showed the highest individualism ranking of all the countries, while Germany ranking above the average but significantly lower on the index scale (rank 15 from 50; index 67 as opposed to 91 from the U.S.) (Hofstede 1983, 1991). Two of seven categories identified by Triandis (1996) are (1) the people's concern about how their decisions could affect others in their collectivity; and (2) the belief in the correspondence of ones own outcomes, both positive and negative, with the outcome of others. These two aspects of collectivism can be seen to be closely related to two constructs in our theoretical model, namely systemic impact and systemic view.

Another cultural dimension that is closely related to the aspect of systemic view is the *analytical versus integrative view*. This dimension was extracted by another cross cultural study that included about 1000 intercultural trainee programs, plus a survey of about 30,000 managers of 30 organizations with locations in 50 different countries (Hampden-Turner and Trompenaars 1993; Trompenaars and Hampden-Turner 1994). The analytical view reflects the extent to which a firm is perceived as a collection of tasks, functions, people, and machines rather than as a group of related persons working together (an integrative viewpoint). Overall, Germany showed a higher tendency towards an integrative view of an organization than the U.S.

Taking these preceding cultural dimensions together, it can be argued that in nations such as Germany, where members of organizations show a tendency towards collectivism and have more of an integrative view of the organization, it matters greatly for managers to consider how the overall IS function will be affected by the sourcing choice. By contrast, managers in countries, such as the U.S., where individual performance is valued higher than collective action, and where managers have more of an analytical view of the organization, the systemic impact of the sourcing choice may reside to the background. This leads to the following proposition:

P1: The negative relationship between comparative in-house advantages in systemic impact and the degree of outsourcing (H3-) is stronger in Germany than in the U.S.

Moreover, German IS managers may be more inclined to consider whether in-house personnel or the staff of external vendors shows more of a systemic view in doing their work:

P2: The negative relationship between comparative systemic view advantages of in-house workers and the degree of outsourcing (H4a-) is stronger in Germany than in the U.S.

Third, in Germany there are a number of unique legal and legitimized institutional constraints that do not exist in the same form in the U.S. For example, in Germany, the protection of employee interests is codified in law. Employee interests are legally supported by the works constitution act ("Betriebsverfassungsgesetz BetrVG") that guarantees the right of employee participation and codetermination ("Mitbestimmung") in social, economic, and personnel matters (Richardi 1990).

Overall, these restrictions suggest that in Germany, major organizational decisions, such IS outsourcing, where personnel and social affairs are affected, are more participative than in the U.S. Accordingly, German managers may be more sensitive to consider the extent to which they have control over the outsourcing process when deciding on IS sourcing than their U.S. colleagues:

P3: The impact between the extent to which IS managers believe that they have control over the outsourcing process and the degree of applications outsourcing is stronger in Germany than in the U.S.

7.5 Method

7.5.1 Data

Data for this study was gathered via a mailed questionnaire survey. Only companies with more than 500 employees were considered. The questionnaires were administered to the highest ranking IS executives of organizations in the USA and Germany. Overall, 180 usable questionnaires were returned. Since the survey included both questions about the development and maintenance of software applications, the sample for this study includes 278 decisions on the sourcing of software applications in Germany and 82 cases in the U.S.

7.5.2 Measures

Each of the constructs from our model was measured with a block of indicators (questionnaire items). Whenever possible, existing measures from prior empirical studies were adopted. An overview of the constructs and exemplified measurement items is provided in Table 7.4. Most of the items were measured on a (positive to negative) five point Likert scale ranging from "strongly agree" to "strongly disagree", with "neither agree nor disagree" as a mid-point. For measures of the *degree of outsourcing*, respondents were asked to provide percentages ranging form 0% to 100%. For the construct *opinion of others*, the semantic differential approach to measurement was adopted (Osgood et al. 1957), where each response is located on an evaluative bipolar (negative to positive) dimension, using a seven point Likert scale. All blocks of indicators were formulated in the reflective mode (Chin 1998a; Chin and Newsted 1999; Fornell 1989). The unit of analysis was the respective application service. The respondents had to answer each question for both the development and the maintenance of application software.

7.6 Analysis and Results

In the following, the results of the model testing for both the U.S. and Germany will be presented. This includes the test of (1) the measurement model and (2) the structural model in both countries, as well as (3) the test of differences in the structural paths between both countries.

7.6.1 Results of Partial Least Squares Estimation

Measurement Model. In order to check whether the indicators of each construct measure what they are supposed to measure, tests for convergent and discriminant validity were performed in both the U.S. and German sample. Before doing any multigroup comparisons, it is always important to first establish the measures perform adequately in both data samples.

In terms of convergent validity (Bagozzi and Phillips 1982), both indicator reliability and construct reliability were assessed (Peter 1981). *Indicator reliability* was examined by looking at the construct loadings. All loadings are significant at the 0.01 level and above the recommended 0.7 parameter value (Significance tests were conducted using the bootstrap routine with 500 resamples (Chin 1998b).

Table 7.4 Questionnaire measures

Construct	Source	Sample Item
Degree of Outsourcing	Based on Dibbern and Heinzl (2004); Teng et al. (1995)	For each of the two IS functions, please estimate the average percentage currently allocated to external service providers in terms of 1. . . . the functions total budget (from 0 to 100%) 2. . . . total person working days. 3. . . . total number of people that participate in doing the work.
Comparative production cost advantage	Based on Ang and Straub (1998)	In doing the actual work required for each of the IS functions 1. . . . our internal staff works more cost efficient than an external service provider. 2. . . . we can realize higher economies of scale internally than an external service provider.
Comparative transaction cost advantage	Based on Ang and Straub (1998)	When delegating i.e. transferring tasks of the particular IS function 1. . . . the costs incurred in negotiating, managing and coordinating are lower within the firm than in case of contracting with an external service provider. 2. . . . less transaction costs are incurred for internal employees than when using an external service provider.
Comparative systemic impact advantage	Informed by the notion of task interdependence (Pfeffer and Salancik 1978; Thompson 1967)	If this IS function is not performed in-house but externally, 1. . . . the integration of this IS function into the overall IS function of our organization is weakened. 2. . . . the synergetic effects to other IS functions will be threatened. 3. . . . the overall performance of our entire IS function will be greatly affected.
Comparative systemic view advantage	See above plus the individualism-collectivism categorization by Hui and Triandis (1986)	In doing the actual work required for each of the IS functions, our own employees tend much more than personnel of external service providers to 1. . . . have a systems view of the organization. 2. . . . have an organization wide perspective of how work in different areas effect one another. 3. . . . consider the task interdependencies in our organization. 4. . . . have an integrated view of the organization.
Outsourcing Process Control	Based on Ajzen (1991); Ajzen and Fishbein (1980)	When it comes to outsourcing this IS function to an external service provider 1. . . . our organization can act unrestrictedly. 2. . . . there are no impediments to our organization.

(continued)

Table 7.4 (continued)

Construct	Source	Sample Item
External Influences	Based on Ajzen (1991); Ajzen and Fishbein (1980)	Persons or groups whose opinion is important to our organization think that outsourcing this particular IS function is 1. …bad - good (-3 to +3). 2. …negative - positive. 3. …harmful - beneficial. 4. …foolish - wise. 5. …illogical - logical. 6. …worthless - valuable.
Firm size	Based on Ang and Straub (1998)	Please estimate your organization's overall number of employees.

Table 7.5 Indicator and construct reliability

Construct	Item	Germany			USA		
		Loading	CR	AVE	Loading	CR	AVE
Degree of Outsourcing	Out1	0.96	0.97	0.93	0.95	0.97	0.91
	Out2	0.96			0.98		
	Out3	0.96			0.94		
Production Cost Advantage	Pc1	0.85	0.86	0.75	0.92	0.90	0.82
	Pc3	0.88			0.89		
Transaction Cost Advantage	Tc1	0.90	0.85	0.74	0.70	0.83	0.71
	Tc4	0.82			0.97		
System Impact Advantage	Impact1	0.89	0.91	0.78	0.92	0.94	0.85
	Impact2	0.89			0.90		
	Impact3	0.86			0.94		
System View Advantage	EmplOrit1	0.77	0.91	0.71	0.77	0.91	0.73
	EmplOri2	0.87			0.77		
	EmplOri3	0.83			0.91		
	EmplOri4	0.89			0.89		
Opinion of Others	Other1	0.92	0.97	0.82	0.93	0.98	0.87
	Other2	0.93			0.92		
	Other3	0.92			0.93		
	Other4	0.89			0.97		
	Other5	0.88			0.96		
	Other6	0.89			0.90		
Process Control	CoPro1	0.94	0.93	0.87	1.00	0.93	0.87
	CoPro2	0.94			0.86		

Construct reliability and validity was tested using two indices: (1) the *composite reliability* (CR) and (2) the *average variance extracted* (AVE). All the estimated indices were above the threshold (Bagozzi and Yi 1988) of 0.6 for CR and 0.5 for AVE (see Table 7.5). Finally, the *discriminant validity* of the construct items

Table 7.6 PLS crossloadings for U.S. sample

	PC	TC	firm size	Out	SysImp	Control	SysView	ExtInfl
Pc1	**0.92**	0.39	0.02	0.36	0.53	0.01	0.17	0.30
Pc3	**0.89**	0.47	0.02	0.31	0.59	0.02	0.36	0.33
Tc1	0.31	**0.70**	0.02	0.11	0.31	0.15	0.34	0.25
Tc4	0.46	**0.97**	0.02	0.30	0.36	0.07	0.35	0.20
NoAll	0.02	0.02	**1.00**	0.16	0.10	0.04	0.06	0.17
Out1	0.28	0.19	0.25	**0.95**	0.08	0.00	0.06	0.29
Out2	0.36	0.33	0.11	**0.98**	0.19	0.02	0.01	0.32
Out3	0.41	0.27	0.11	**0.94**	0.25	0.04	0.01	0.37
Impact1	0.62	0.40	0.16	0.22	**0.92**	0.17	0.37	0.34
Impact2	0.50	0.31	0.00	0.16	**0.90**	0.11	0.30	0.44
Impact3	0.56	0.35	0.09	0.14	**0.94**	0.07	0.44	0.40
CoPro1	0.01	0.10	0.04	0.02	0.13	**1.00**	0.10	0.01
CoPro2	0.11	0.10	0.03	0.00	0.09	**0.86**	0.04	0.03
EmplOri1	0.19	0.28	0.12	0.09	0.34	0.19	**0.77**	0.28
EmplOri2	0.34	0.44	0.05	0.03	0.31	0.01	**0.84**	0.28
EmplOri3	0.25	0.38	0.12	0.11	0.40	0.04	**0.91**	0.35
EmplOri4	0.19	0.23	0.08	0.08	0.35	0.12	**0.89**	0.28
Other1	0.32	0.25	0.17	0.28	0.39	0.05	0.28	**0.93**
Other2	0.35	0.21	0.23	0.28	0.37	0.07	0.24	**0.92**
Other3	0.31	0.12	0.14	0.24	0.42	0.05	0.31	**0.93**
Other4	0.36	0.27	0.15	0.36	0.42	0.05	0.34	**0.97**
Other5	0.34	0.26	0.17	0.34	0.39	0.02	0.41	**0.96**
Other6	0.26	0.21	0.08	0.37	0.37	0.10	0.36	**0.90**

was assured by looking at the cross-loadings. They are obtained by correlating the component scores of each latent variable with both their respective block of indicators and all other items that are included in the model (Chin 1998b). In Tables 7.6 and 7.7, in the Appendix, the cross loadings for both the USA and Germany are presented. The loadings on their respective constructs are shadowed. Moving across the rows reveals that each item loads higher on its respective construct than on any other construct. Going down a column also shows that a particular constructs loads highest with its own item. Taken together, this implies discriminant validity for both samples.

Structural Model. Having gained confidence that the measures work appropriate for both the U.S. and German sample, the next step is to test the explanatory power of the entire model on IS sourcing as well as the predictive power of the independent variables in both countries. The explanatory power is examined by looking at the *squared multiple correlations* (R^2) of the main dependent variable, the degree of IS outsourcing. As can be inferred from Fig. 7.3, in Germany 33% ($R^2 = 0.33$) of the variation in the degree of outsourcing are explained by the independent variables, while in the U.S. 27% ($R^2 = 0.27$) are accounted for. The hypotheses are tested by examing the magnitude of the standardized parameter estimates between constructs together with the corresponding t-values that indicate the level of significance.

Table 7.7 PLS crossloadings for German sample

	PC	TC	firm size	Out	SysImp	Control	SysView	ExtInfl
Pc1	**0.85**	0.57	0.05	0.34	0.40	0.16	0.44	0.25
Pc3	**0.88**	0.44	0.10	0.38	0.49	0.12	0.42	0.33
Tc1	0.53	**0.90**	0.12	0.36	0.33	0.14	0.33	0.30
Tc4	0.45	**0.82**	0.03	0.27	0.40	0.06	0.39	0.29
NoAll	0.09	0.07	**1.00**	0.01	0.03	0.01	0.13	0.00
Out1	0.40	0.36	0.03	**0.96**	0.41	0.05	0.35	0.36
Out2	0.41	0.37	0.01	**0.96**	0.43	0.04	0.38	0.32
Out3	0.38	0.36	0.02	**0.96**	0.41	0.04	0.37	0.38
Impact1	0.51	0.41	0.03	0.38	**0.89**	0.24	0.46	0.21
Impact2	0.46	0.36	0.03	0.41	**0.89**	0.14	0.44	0.28
Impact3	0.40	0.34	0.02	0.35	**0.86**	0.16	0.41	0.22
CoPro1	0.16	0.11	0.03	0.05	0.18	**0.97**	0.17	0.05
CoPro2	0.14	0.12	0.07	0.03	0.21	**0.90**	0.17	0.05
EmplOri1	0.34	0.36	0.08	0.23	0.40	0.15	**0.77**	0.18
EmplOri2	0.47	0.39	0.17	0.38	0.41	0.08	**0.87**	0.31
EmplOri3	0.41	0.31	0.03	0.33	0.39	0.22	**0.83**	0.17
EmplOri4	0.44	0.34	0.14	0.33	0.46	0.15	**0.89**	0.19
Other1	0.37	0.37	0.03	0.34	0.28	0.07	0.25	**0.92**
Other2	0.35	0.35	0.03	0.33	0.27	0.07	0.27	**0.93**
Other3	0.33	0.31	0.01	0.34	0.27	0.03	0.22	**0.92**
Other4	0.26	0.28	0.03	0.33	0.22	0.09	0.22	**0.89**
Other5	0.23	0.25	0.03	0.31	0.22	0.06	0.18	**0.88**
Other6	0.27	0.32	0.04	0.34	0.21	0.02	0.22	**0.89**

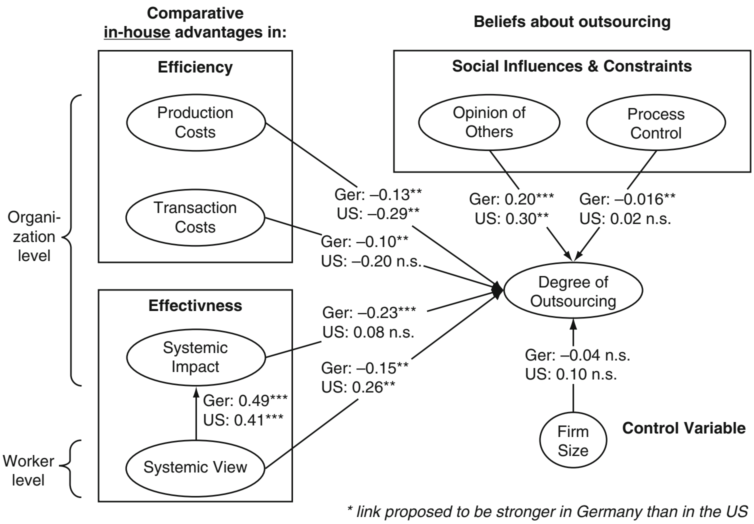

Fig. 7.3 Structural model findings for Germany and the U.S.

Table 7.8 PLS results for structural model and group comparisons

Independent Variable	Dependent Variable	Hypothesis	Germany $n = 278$		USA $n = 82$		Country Difference	
			Path	P-values	Path	P-values	Path	P-value
Production cost advantage	Degree of Outsourcing	$H1(-)$	−0.13**	3.1	−0.29**	2.0	0.17 n.s.	13.0
Transaction cost advantage	Degree of Outsourcing	$H2(-)$	−0.10**	4.8	−0.20 n.s.	10.9	0.10 n.s.	25.2
Systemic impact advantage	Degree of Outsourcing	$H3(-)$	−0.23***	<0.1	0.08 n.s.	29.5	**−0.31****	**2.5**
Systemic view advantage	Degree of Outsourcing	$H4a(-)$	−0.15**	2.4	0.26**	1.7	**−0.40*****	**0.3**
Systemic view advantage	Systemic impact advantage	$H4b(+)$	0.49***	<0.1	0.41***	<0.1	0.08 n.s.	17.1
External influence	Degree of Outsourcing	$H5(+)$	0.20***	<0.1	0.30**	1.0	−0.10 n.s.	20.9
Outsourcing Process Control	Degree of Outsourcing	$H6(+)$	−0.16**	1.3	0.02 n.s.	41.7	**−0.18***	**7.9**
Firm size	Degree of Outsourcing	$H7$	−0.04 n.s.	14.0	0.10 n.s.	25.8	−0.14 n.s.	12.0

t-values were obtained through the bootstrap routine (Chin 1998b). An overview of the results can be inferred from Table 7.8. Moreover, Fig. 7.3 shows a graphical representation of the findings for Germany and the U.S.

The findings show solid support for the efficiency and effectiveness hypotheses in Germany. All of the path coefficients show the expected negative sign and are significant at the 0.05 (**) or 0.01 (***) level. Notably, perceived comparative in-house advantages in the systemic impact have the strongest impact ($H3 : -0.23$, $t = 3.67$). The impact of Social Influences & Constraints is less consistent. While solid support can be found for the impact of influential others on the degree of outsourcing ($H5 : 0.20$, $t = 3.93$), the link between decision control and outsourcing is negative instead of positive as predicted in the model. Moreover, firm size has no impact. In the U.S., the opposite was found, that comparative advantages of in-house workers in the systemic view are positively related to the degree of outsourcing and not negatively, as predicted. Moreover, in contrast to Germany, no evidence can be found for the significant impact of comparative transaction cost advantages and systemic impact advantages, as well as for decision control and firm size.

Significance of Group Differences. The question is, however, whether the observed differences between Germany and the U.S. are significant and whether those differences are in line with the proposed cultural differences ($P1 - P3$). This can be inferred from the right column of Table 7.8. It shows the level of probability with which the hypotheses that the parameter estimates equal zero (i.e., that the Null-hypothesis) is true. This probability (scaled from 0 to 100) is also called critical distance and should be limited to 1% ($P < 1$), 5% ($P < 5$), or 10% ($P < 10$) (Mohr 1991).

The results show that the path coefficient from systemic impact advantage to degree of outsourcing (H3) in the structural model for Germany is significantly stronger ($P = 2.5$) than the corresponding path in the structural model for the U.S., supporting P1 at the 0.05 level of significance. Moreover, the link between outsourcing process control and degree of outsourcing is significantly stronger ($P = 7.9$) in Germany than in the U.S., supporting P3 at the 0.1 level of significance. Finally, P2 is supported partially. It was proposed that the negative link between systemic view advantage and degree of outsourcing were stronger in Germany than in the U.S. However, the results show that not the strength, but the direction of that link is significantly different between Germany and the U.S. It is negative in Germany, while positive in the U.S.

Given the results of our earlier simulation, we might conjecture that the asymmetry in sample size between Germany and U.S. may impact the p-value estimate for P3. While it was found to be significant at the 0.1, it would not be at the 0.05 level of significance. The Germany size at $n = 278$ is larger than our simulated size of 150 as was the U.S. sample of 82 being slightly larger than the 75 setting we tested. At an exact 150 versus 75 group sample difference, recall that we found the power to range from 65 to 68. Thus, we might conjecture that had the U.S. sample been closer to 150, we would have obtained a multi-group p-value at 0.05.

7.6.2 Results of AMOS Estimation

The AMOS results of the structural model for Germany and the U.S., as well as the test results for country differences in the structural model are depicted in Table 7.9. The focus is on comparing the level of significance for the differences in structural paths as provided by AMOS with those from PLS. The comparison reveals strong agreement between the PLS and AMOS results. Just like in PLS, only the relationships from H3, H4, and H6 show significant differences between both countries. There are only differences in the level of significance, e.g. the country difference for the path coefficient from systemic view advantage to degree of outsourcing is significant at the 0.01 level in Germany ($P = 0.3$) and at the 0.1 level in the U.S. ($P = 8.9$).

Table 7.9 Amos results for structural model and group comparisons

Independent Variable	Dependent Variable	Hypothesis	Germany $n = 278$		USA $n = 82$		Country Difference	
			Path	P-value	Path	P-value	Path	P-value
Production cost advantage	Degree of Outsourcing	$H1(-)$	−0.16 n.s.	60.2	−0.20 n.s.	25.8	0.04 n.s.	100.0
Transaction cost advantage	Degree of Outsourcing	$H2(-)$	−0.10 n.s.	71.3	−0.38*	4.9	0.29 n.s.	37.1
Systemic impact advantage	Degree of Outsourcing	$H3(-)$	−0.27***	<0.1	0.05 n.s.	65.2	**−0.32**** 	**1.1**
Systemic view advantage	Degree of Outsourcing	$H4a(-)$	−0.10 n.s.	37.2	0.39**	0.7	**−0.49***	**8.9**
Systemic view advantage	Systemic impact advantage	$H4b(+)$	0.60***	<0.1	0.48***	<0.1	0.12 n.s.	52.7
External influence	Degree of Outsourcing	$H5(+)$	0.18**	0.4	0.29*	1.1	−0.12 n.s.	100.0
Outsourcing Process Control	Degree of Outsourcing	$H6$	−0.19**	0.2	−0.004 n.s.	92.7	**−0.18****	**4.0**
Firm size size	Degree of Outsourcing	$H7$	−0.04 n.s.	39.6	0.03 n.s.	72.8	−0.08 n.s.	40.3

7.7 Discussion and Summary

This paper has presented results from two PLS based MGSEM studies. First, it provides initial insights into how this new procedure for multi-group comparison using PLS performs with simulated data. This was intended to provide an initial sense of the sample sizes required to achieve adequate power. Second, it empirically provides a didactic example of a confirmatory test on cross-cultural differences related to IS outsourcing. Specifically, we provide an example of how social scientists might introduce three propositions on differences between two countries.

In terms of the cross cultural results, we showed that some of the factors that explain variations in the degree of application software outsourcing are the same in both countries, while other influences differ significantly between both countries.

Commonalities. In both the U.S. and German sample, differences in production costs between in-sourcing and outsourcing as well as the opinion of influential others have a significant impact on the sourcing of application services. Both findings are in line with the empirical literature on IS outsourcing. The results also show that it is not a strictly rational decision process that occurs within the boundaries of the IS department, but rather a participative process that recognizes the opinion of external others.

Country Differences. While efficiency matters both in the U.S. and Germany, effectiveness criteria were found to be treated differently. First of all, while perceived in-house advantages in the *systemic impact* of an IS function were found to impede the extent to which application services are outsourced in Germany, the relationship was found to be irrelevant in the U.S. This obvious country difference is consistent with our perspective that German managers have more of an integrative view of the organization, where the firm is viewed as a group of related persons working together. By contrast, U.S. managers may see the firm as a collection of tasks, functions, people, and machines that can be changed and exchanged more flexibly, without leading to severe consequences for overall firm performance (Hampden-Turner and Trompenaars 1993, p. 18).

Second, the results show that in both countries, *systemic view* is an important predictor of the extent to which application services are outsourced, however, with different directional impacts. Germany, with a more integrative view and collectivist culture is less likely (more negative path) to outsource an IS function if they perceive a systemic view advantage exists for their company employees relative to outsourced workers. In contrast, the collectivist nature is likely viewed potentially as a hindrance in the U.S. The analytical nature of the U.S. workforce emphasizes compartmentalized effort and rotation/shifting of workers when required. Thus, the more systemic or collectivistic a CIO may perceive his or her company to be, the greater the desire to minimize this culture through the use of an external workforce.

Another relationship that was found to be culturally sensitive is the link between *outsourcing decision control* and degree of outsourcing. It was proposed, that a higher level of perceived control over the outsourcing process would be positively related with the degree of outsourcing and that this link would be stronger in Germany than in the U.S. Interestingly, there was a significant difference in the impact of that link between Germany and the U.S. But unexpectedly, that link was positive, instead of negative in Germany, while insignificant in the U.S. In other words, German organizations show a higher level of outsourcing if IS managers do not believe that they have full control over all necessary activities associated with outsourcing. A similar reversed link, albeit in a different organizational context, was also found in the study from Cordano and Frieze Hanson (2000, p. 637). From their point of view, this finding may be explained by the limited power of managers, which hinders them to act in accordance with their beliefs.

Overall, the PLS MGSEM analysis is shown to provide useful information for researchers interested in applied areas such as cross cultural studies. Using this technique, we were able to determine that cultural differences play a substantial role in IS sourcing decisions and that it is necessary to recognize that behavioral and institutional differences between countries can significantly limit the generalizability of mid-range theories of IS sourcing. In terms of our Monte Carlo simulation, the results, while not surprising, provides a sense of how the effect size, sample size, normality, and magnitude of prediction impacts the ability to detect an effect. A future study might involve a more complete assessment of the effect of asymmetry in the sample size between the two groups with the combined cases fixed at the same number. Furthermore, we'd recommend a comparison of how the PLS algorithm compares with a simple summed regression. Our initial test with an asymmetric sample set of 150 and 75, non-normal condition, and 0.7 and 0.4 path differences resulted in the PLS algorithm providing a 10 percent higher level in statistical power.

In summary, this paper attempted to illustrate the appropriateness of using a new non-parametric procedure for conducting MGSEM analysis using PLS. As noted earlier, such an approach employing randomization tests should not be viewed as alternatives to parametric statistical tests, rather they should be considered as those tests for that particular empirical form being examined. Thus, normal theory MGSEM may be viewed as approximations. This is an extremely important property in the case of both data distributions and nonrandom samples common in surveys, which would otherwise invalidate the use of parametric statistical tables (e.g., t or F tables). Nevertheless, in the case of our outsourcing data set, we did find remarkably similar results with the AMOS analysis, which provides greater confidence in a methodological convergent validity sense. Unfortunately, due to page and analytical constraints, comparison of our Monte Carlo results with those obtained using AMOS or similar covariance based MGSEM analysis was not performed. What would be useful in the future is to generate such data conforming to a model with varying levels of non-normality (both leptokurtic and platykurtic and left and right skewed) to see how both methods perform.

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