# Chapter 10
# Applying Multigroup Analysis in PLS-SEM: A Step-by-Step Process

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**Abstract** This book chapter identifies the importance and different uses for multigroup analysis, such as research interests in cross-cultural or gender differences. Multigroup analysis via partial least squares structural equations modeling, which tests a single structural relationship at a time, is an effective way to evaluate moderation across multiple relationships versus standard moderation. Step-by-step instructions and guidelines using SmartPLS 3.0 are provided using a sample dataset. The instructions include an assessment of the measurement characteristics of the constructs by including the MICOM procedure, which adds an additional level of accuracy. Examples of both positive and negative outcomes as well as potential solutions to problems are provided in order to help users understand how to apply multigroup analysis to their own dataset. By using multigroup analysis, researchers are able to uncover differences of subsamples within the total population that is not evident when examined as a whole. Researchers having the ability to run multigroup analysis considerably improve the likelihood of identifying significant and meaningful differences in various relationships across group-specific results.

## 10.1 Introduction

Many research studies report their findings based on an analysis of a single population. Unfortunately, studies that pool data as a single population fail to assess whether there are significant differences across two or more subgroups of data (Chin and Dibbern 2010). As a result, interpreting results from a single population can be misleading (Sarstedt et al. 2016a). But if categorical moderating variables are available in the dataset, group-specific path coefficient estimates that are significantly different can be identified efficiently, thereby accounting for observed heterogeneity (Sarstedt et al. 2011) and minimizing the potential for misrepresentation of the results (Sarstedt et al. 2009).

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Multigroup analysis (MGA) or between-group analysis as applied using partial least squares structural equations modeling (PLS-SEM) is a means of testing predefined data groups to determine if there are significant differences in group-specific parameter estimates (e.g., outer weights, outer loadings, and path coefficients) (Hair et al. 2014a; Henseler and Chin 2010). By applying MGA, researchers are therefore able to test for differences between two identical models for different groups. The ability to identify the presence or absence of multigroup differences can be based on either a bootstrapping or permutation result for every group. Partial least squares structural equation modeling multigroup analysis (PLS-MGA) can be instrumental, therefore, in identifying differences among a priori-specified groups within the dataset (e.g., Hair et al. 2014a; Horn and McArdle 1992; Keil et al. 2000).

MGA is particularly useful for globally focused research, such as cross-cultural studies. For example, the method has been used to compare antecedents of market orientation across three countries (Brettel et al. 2008), to test the determinants and outcomes of cultural intelligence (Schlagel and Sarstedt 2016), and to examine company stakeholder orientation in five European countries (Patel et al. 2016). Alternatively, MGA has been used to understand the differences between consumers with high vs. low tendency toward loyalty (Picon-Berjoyo et al. 2016). This type of analysis enabled researchers to uncover differences between groups such as the low impact of switching costs for individuals exhibiting high loyalty (Picon-Berjoyo et al. 2016). Additionally, by gaining insight into group differences, a more accurate assessment is conducted, and strategy implementation based on the outcomes can be more specific for the heterogeneous groups in the data. Finally, the differences can highlight the error associated with incorrectly treating these subpopulations as a single homogeneous group (Schlagel and Sarstedt 2016).

MGA via PLS-SEM is an efficient way to assess moderation across multiple relationships as opposed to standard moderation, which examines a single structural relationship at a time (Hair et al. 2010, 2011, 2012c). According to Hair et al. (2014a, p. 246) "...this approach offers a more complete picture of the moderator's influence on the analysis results as the focus shifts from examining its impact on one specific model relationship to examining its impact on all model relationships."

Continuous moderators are relatively easy to examine in PLS-SEM, but deserve special attention. They are often measured with multiple items, which will increase the predictive validity compared to single-item measurements (Diamantopoulous et al. 2012; Sarstedt et al. 2016b). Within the context of moderation, this can be particularly problematic as moderation is usually associated with rather limited effect sizes (Aguinis et al. 2005). As a result, any lack of predictive power makes it more difficult to identify significant relationships. Moreover, when modeling moderating effects, the measurement model construct is contained in the model twice. The construct is the moderator variable itself in addition to being in the interaction term. The result amplifies the limitations of single-item measurement when used to execute moderation.

## 10.2 Overview of Steps for Running MGA in PLS-SEM

Comparison of group-specific outcomes can be undertaken in three simple to apply steps, thus increasing the rigor of the data analysis and reducing misleading results. An overview of the steps (Fig. 10.1) is provided as an introduction to the process that draws upon information from Hair et al. (2014a). The overview is followed by an in-depth discussion of each step, including examples for an easy application to your own dataset. To facilitate the discussion, the SmartPLS software is used to describe the process (Ringle et al. 2015).

*Step 1* involves generating data groups that are based on the categorical variable of interest [e.g., gender (Rutherford et al. 2011), country of origin (Brettel et al. 2008), urban vs. rural (Rasoolimanesh et al. 2016)]. Data groups are generated in SmartPLS by double-clicking on the data for the model of interest and selecting "Generate Data Groups." A name can be specified for the group being generated, and then, the group is established by selecting the categorical variable of interest from your dataset. For example, if your theory or judgment suggests that males and females produce different results, then your analysis would be set up to examine gender. For more extensive analyses, more than one categorical variable can be selected (e.g., gender and marital status), which would create multiple outcome groups (single female, single male, married females, married males, etc.). For the example in this chapter, however, a single categorical variable will be used.

After specifying the variable of interest, the data groups are generated. Output is provided on a separate tab labeled "data groups." The groups are listed based on the coding of your data. Additionally, the number of records for each data group is provided. Each line item can be edited to rename the subgroup a more identifiable name [e.g., female, rather than gender (1.0)]. Once the data is subdivided, it is important to confirm that the new subgroups are large enough and comparable in size so as not to introduce error (Becker et al. 2013; Hair et al. 2014a). The minimum sample size recommendation in PLS-SEM has differing views by researchers. One view is that the number of responses for each subgroup should equal (or be comparable to) the sample size recommendations for a statistical power of 80%, as recommended by Cohen (1992) and Hair et al. (2014a). Groups with fewer observations than that recommended for a statistical power of 80% in most situations should not be used (Table 10.1).

Alternatively, Kock and Hadaya (2016) analyze the gamma-exponential method and the inverse square root method. They demonstrate that while the gamma-exponential method is much more complex of an application, for PLS-SEM users who are not methodological researchers, the inverse square root method may be a simpler equation for minimum sample size estimations at the early stage of the research design (Table 10.2) (Kock and Hadaya 2016). Although the method leads to a small overestimation, the slight imperfection allows for a safe minimum sample size (Kock and Hadaya 2016).

*Step 2* involves using the three-step procedure to analyze the measurement invariance of composite models (MICOM) (Henseler et al. 2016). Measurement

**Fig. 10.1** Guidelines for running MGA in PLS-SEM

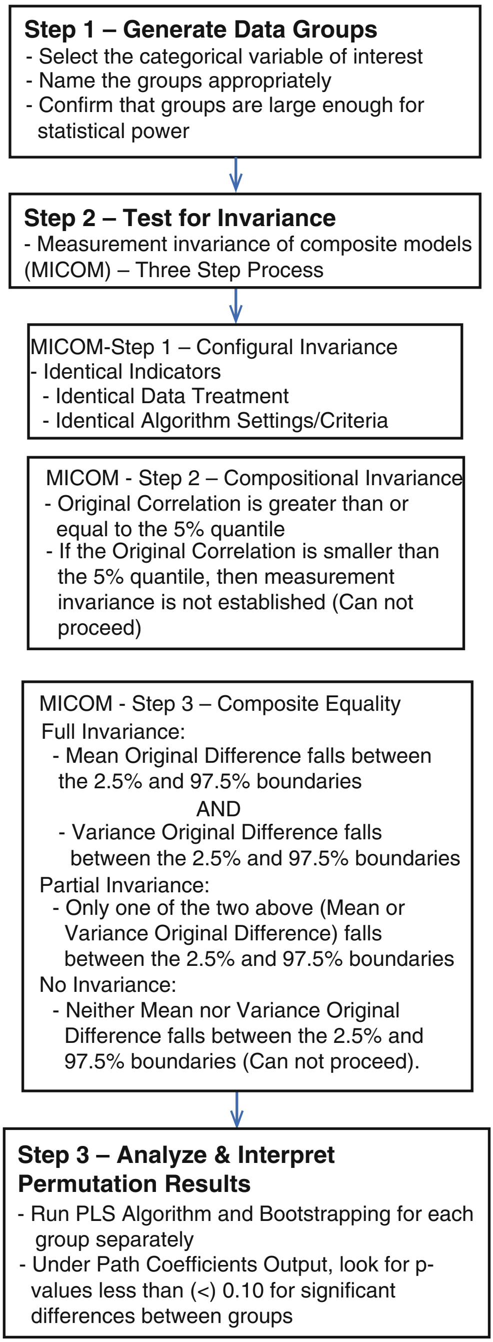

**Table 10.1** Sample size recommendation in PLS-SEM for a statistical power of 80% (Cohen 1992; Hair et al. 2014a)

| Maximum number of arrows pointing at a construct | Significance level | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1% | | | | 5% | | | | 10% | | | |
| | Minimum $R^2$ | | | | | | | | | | | |
| | 0.10 | 0.25 | 0.50 | 0.75 | 0.10 | 0.25 | 0.50 | 0.75 | 0.10 | 0.25 | 0.50 | 0.75 |
| 2 | 158 | 75 | 47 | 38 | 110 | 52 | 33 | 26 | 88 | 41 | 26 | 21 |
| 3 | 176 | 84 | 53 | 42 | 124 | 59 | 38 | 30 | 100 | 48 | 30 | 25 |
| 4 | 191 | 91 | 58 | 46 | 137 | 65 | 42 | 33 | 111 | 53 | 34 | 27 |
| 5 | 205 | 98 | 62 | 50 | 147 | 70 | 45 | 36 | 120 | 58 | 37 | 30 |
| 6 | 217 | 103 | 66 | 53 | 157 | 75 | 48 | 39 | 128 | 62 | 40 | 32 |
| 7 | 228 | 109 | 69 | 56 | 166 | 80 | 51 | 41 | 136 | 66 | 42 | 35 |
| 8 | 238 | 114 | 73 | 59 | 174 | 84 | 54 | 44 | 143 | 69 | 45 | 37 |
| 9 | 247 | 119 | 76 | 62 | 181 | 88 | 57 | 46 | 150 | 73 | 47 | 39 |
| 10 | 256 | 123 | 79 | 64 | 189 | 91 | 59 | 48 | 156 | 76 | 49 | 41 |

**Table 10.2** Alternative sample size recommendation in PLS-SEM using inverse square root method (Kock and Hadaya 2016)

| Maximum number of arrows pointing at a construct | Minimum $R^2$ in the model | | | |
|---|---|---|---|---|
| | 0.10 | 0.25 | 0.50 | 0.75 |
| 2 | 110 | 52 | 33 | 26 |
| 3 | 124 | 59 | 38 | 30 |
| 4 | 137 | 65 | 42 | 33 |
| 5 | 147 | 70 | 45 | 36 |
| 6 | 157 | 75 | 48 | 39 |
| 7 | 166 | 80 | 51 | 41 |
| 8 | 174 | 84 | 54 | 44 |
| 9 | 181 | 88 | 57 | 46 |
| 10 | 189 | 91 | 59 | 48 |

invariance (also referred to as equivalence) is a means of determining if the measurement models specify measures of the same attribute under different conditions (Henseler et al. 2015, 2016). This is a critical issue that must be addressed in MGA. Testing for measurement invariance determines "whether or not, under different conditions of observing and studying phenomena, measurement models yield measures of the same attribute" (Henseler et al. 2015, p. 117). When measurement invariance is established, researchers can conclude that different model estimation parameters are not the result of the distinct content or meaning of the latent variables/constructs that comprise the measurement model of any one group (Chin and Dibbern 2010; Henseler et al. 2016). Additionally, by not establishing invariance in the measurement model constructs, measurement error may be introduced leading to biased results (Hult et al. 2008). Therefore, when analyzing differences between groups, type II errors are minimized (Hult et al. 2008), and the resulting differences are the result of actual group-specific differences in the parameters and not measurement invariance (Henseler et al. 2016). The MICOM procedure compares group parameters and identifies if there is no measurement invariance, partial measurement invariance, or full measurement invariance (Henseler et al. 2016).

In *Step 3*, results of the statistical tests for multigroup comparisons are assessed. A number of approaches can be used to compare the path coefficients of the group SEMs. Three tests are included in the SmartPLS MGA (PLS-MGA) option—Henseler et al.'s (2009) PLS-MGA procedure, parametric, and Welch-Satterthwaite. A fourth approach to making group comparisons—permutation (Hair et al. 2014a; Henseler et al. 2016)—is a separate option in the SmartPLS software. The parametric test results tend to be liberal and subject to type I errors and are also limited because they are based on distribution assumptions that are not consistent with the nonparametric PLS-SEM method (Hair et al. 2017b; Sarstedt et al. 2011). The Welch-Satterthwaite test is a variant of the parametric test, but does not assume equal variances when comparing the means of two groups. The Henseler et al.'s PLS-MGA procedure (Henseler et al. 2009) and the permutation test are both nonparametric approaches. The Henseler et al.'s PLS-MGA procedure (Henseler et al. 2009) approach is included in the regular multigroup option. The Henseler et al.'s PLS-MGA procedure (Henseler et al. 2009) derives a probability value for a one-tailed test by comparing each bootstrap estimate of one group to all the bootstrap estimates of the same parameter in the other group (Hair et al. 2011). While considered to be an appropriate test, the results may be a bit challenging to interpret due to the one-tailed test. Moreover, since bootstrap distributions are not necessarily symmetrical, the Henseler et al.'s PLS-MGA procedure (Henseler et al. 2009) cannot be used to test two-tailed hypotheses. In contrast, the permutation test is a separate option and is run during Step 2 of the analysis as part of the test for measurement invariance. The output of the path coefficients from the measurement invariance option is another means of comparing the path coefficients of the subgroups. The permutation test is more conservative than the parametric test and controls well for type I error. Moreover, most researchers recommend the permutation test (Hair et al. 2017b); therefore, that approach is examined in this chapter.

## 10.3 Example Application of PLS-MGA

As a means of providing clarity for the execution of these steps, examples are provided for each step. The examples include output and explanation for the results that are the primary focus of the analysis. The next section revisits each step in the PLS-MGA process and provides specific details and interpretation.

### 10.3.1 Step 1: Generate Data Groups

Before executing an MGA, you must generate groups in your data. When you do this, the analysis is able to statistically assess the differences between the group-specific parameters, most often path coefficients resulting from different subpopulations (Brettel et al. 2008; Grewal et al. 2008). This procedure enables researchers to evaluate observed heterogeneity in model relationships (Lohmöller 1989).

MGA is similar to moderator analysis where the moderator is a categorical variable, and it is anticipated that the moderator will affect at least one and perhaps all of the model relationships (Sarstedt et al. 2011). The models in Fig. 10.2 examine the differences between female and male sales representatives. The question to be investigated is "Do the sales roles of females and males differ with regard to autonomy, skill discrepancy, and cognitive engagement?"

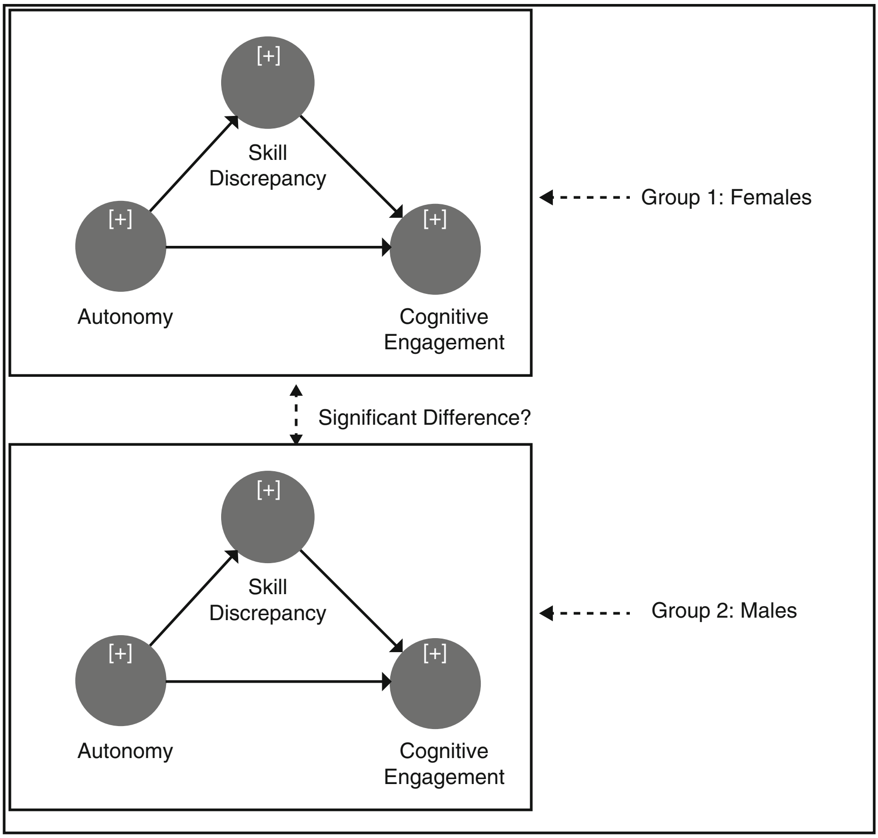


**Fig. 10.2** Categorical variable PLS-MGA example

The data used for the examples in this chapter was collected via a Qualtrics online panel of business-to-business salespeople. After removal of one outlier and two straight-line responses, the final sample size is 235. The outlier identified himself or herself as a business-to-business salesperson, but when responding to the number of customers, these respondents stated 10,000 customers while the remaining respondents identified a number in the range of 1–400. Since a portion of the research is related to levels of customer service, this participant was identified as being more closely related to retail rather than business to business and was therefore removed. The questionnaire employed established scales, when available. Modifications were made to adapt the scales to the context of sales.

Recall that the sample sizes of the subpopulations must be large enough to meet statistical power guidelines. Therefore, groups that do not meet sample size recommendations should not be utilized. You may consider combining one or more smaller groups with another group if the groups exhibit similar characteristics.

For this example, the sample size for the female subgroup is 101 and for the male subgroup is 134. Each of these subpopulations exceeds the minimum for the theoretical model in Fig. 10.2 that has two arrows pointing at a construct—i.e., cognitive engagement (10% with a minimum $R^2$ of $0.10 = 88$). In order to exceed the minimum $R^2$ of 0.10 at a 5% significance level, both the male and female subgroups would need to exceed 110 (Hair et al. 2014a). Ultimately, subsamples of 158 for both males and females would provide a significance level of 1%.

The two subpopulations (male and female) meet the minimum sample size criteria, but are not the same size. While two subpopulations do not have to be exactly the same size, they do need to be comparable in size. The guideline to consider regarding group sample size differences is when one group is more than 50% larger than the other, the difference is likely to bias the results of the statistical test of differences (Hair et al. 2016a). The recommended procedure when confronted with groups that differ substantially in sizes, therefore, is to randomly withdraw respondents from the larger subgroup (males) to make the groups comparable in size, with each subpopulation totaling 101 (Hair et al. 2016a). Another option, when possible, is to collect more data for the subgroup with the smaller sample size. When the sample sizes of the groups are considered comparable, it is appropriate to move to Step 2. Note that the groups are not required to be the exact same sample size but should be comparable to avoid producing biased results (Hair et al. 2017b).

The theoretical model for the example (Fig. 10.2) includes three constructs: autonomy, skill discrepancy, and cognitive engagement. Autonomy measures the extent to which salespeople have the freedom to determine which customers are pursued or not, how resources should be distributed among the firm's customers, as well as which customer relationships to continue and which to end. The autonomy construct had 13 items and was measured using 7-point Likert-type scales (rho_A = 0.954 male sample, 0.973 female sample; AVE = 0.600 male sample, 0.608 female sample). The skill discrepancy construct had four items and was measured using 11-point (0–10) Likert-type scales (rho_A = 0.915 male sample, 0.860 female sample; AVE = 0.785 male sample, 0.69 female sample). Finally, the cognitive engagement construct had five items measured using 11-point Likert-type scales (rho_A = 0.940 male sample, 0.942 female sample; AVE = 0.773 male sample, 0.797 female sample) (Table 10.3). In addition to meeting recommended guidelines for reliability and convergent validity, the heterotrait-monotrait ratio (HTMT) was used to assess discriminant validity. All measures were well below the 0.90 thresholds, thus indicating discriminant validity (Hair et al. 2014a) (Table 10.4).

To generate the subpopulations within the dataset in SmartPLS, go to the Project Explorer window and identify the dataset your model is using. Next, double-click on the data icon for your model. The "Generate Data Groups" icon will appear at the top of your SmartPLS screen. You will need to assign an initial name for your groups. The name can be edited to be more specific once the subpopulations have been established. Next, the categorical variable of interest is selected in the group column section (see Fig. 10.3). Note that more than one group variable can be included in the analysis (e.g., gender and age), but only one group variable will be discussed in the example for this chapter. The "Prune groups" option can remain at the default of 10 for the initial processing. Groups can be manually pruned (eliminated) after they are generated if the subpopulation is not large enough to meet statistical power guidelines (Cohen 1992; Hair et al. 2014a).

As noted earlier, the categorical variable we are using in this analysis is gender. After specifying the overall group name of gender, the output displayed in the data groups tab indicates two groups were generated (see Fig. 10.4). The first group is specified as Group_Gender_Q31_Gender(1.0) and shows the number of records (responses) associated with that group. The second group is specified as Group_Gender_Q31_Gender(2.0) and shows the number of respondents associated with this particular group. To rename these initial group labels, highlight (click on) the row for the first group, and two buttons will appear on the right side of the row (Delete and Edit). By selecting the edit button, the group name can be edited for this subpopulation. In this case, the coding for gender 1.0 represents the male portion of the population. Therefore, the group name is revised to read male (see Fig. 10.5). Similarly, Group_Gender_Q31_Gender(2.0) is renamed female.

### *10.3.2 Step 2: Test for Invariance*

The next step in the process is to test for measurement invariance. To test for measurement invariance in PLS-SEM, the MICOM procedure is executed (Henseler et al. 2016). This procedure requires three steps to test for configural and compositional invariance, as well as equality of composite mean values and variances (Henseler et al. 2016).

The first step in the MICOM procedure involves examining configural invariance (Henseler et al. 2016). The assessment of configural invariance consists of an evaluation of the measurement models for all groups to determine if the same basic factor structure exists in all the groups (same number of constructs as well as items for those constructs). Establishing configural invariance involves the fulfillment of

**Table 10.3** Outer loadings, rho_A, and AVE for example application

| | Group | | | Males | | | Females | | |
|---|---|---|---|---|---|---|---|---|---|
| | Outer loadings | rho_A | AVE | Outer loadings | rho_A | AVE | Outer loadings | rho_A | AVE |
| **Autonomy (SD = 1, SD = 7)** | | 0.954 | 0.603 | | 0.954 | 0.600 | | 0.973 | 0.608 |
| I can choose not to pursue a prospective customer | 0.723 | | | 0.691 | | | 0.791 | | |
| I can decide on my own whether or not to pursue a prospective customer | 0.737 | | | 0.664 | | | 0.818 | | |
| I have control over which prospects pursue | 0.796 | | | 0.764 | | | 0.852 | | |
| I am empowered to determine which customers to pursue or not pursue | 0.803 | | | 0.805 | | | 0.813 | | |
| I have control over which of my customers are designated as *most* important by my firm | 0.838 | | | 0.843 | | | 0.816 | | |
| I have control over which of my customers are designated as *least* important by my firm | 0.725 | | | 0.678 | | | 0.758 | | |
| I have significant autonomy in determining which of my customers should receive preferential treatment from the firm | 0.808 | | | 0.839 | | | 0.737 | | |
| I can decide on my own whether or not one of my customers should receive a high priority status | 0.747 | | | 0.837 | | | 0.605 | | |
| I am empowered to lower my customers' priority status within my firm | 0.721 | | | 0.780 | | | 0.624 | | |
| I have significant autonomy in determining which customer relationships to end | 0.824 | | | 0.826 | | | 0.815 | | |
| I can choose not to end a relationship with a particular customer | 0.783 | | | 0.785 | | | 0.805 | | |
| I can decide on my own whether or not should terminate the relationship with one of my customers | 0.739 | | | 0.706 | | | 0.777 | | |
| I have control over which of my customer relationships to continue | 0.839 | | | 0.817 | | | 0.877 | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Skill discrepancy (SD = 0, SA = 10)** | | 0.889 | 0.744 | | 0.915 | 0.785 | | 0.860 | 0.690 |
| My job requires me to learn new things | 0.870 | | | 0.885 | | | 0.842 | | |
| My job requires me to be creative | 0.860 | | | 0.880 | | | 0.814 | | |
| My job requires a high level of skill | 0.844 | | | 0.861 | | | 0.854 | | |
| I get to do a variety of different things on my job | 0.876 | | | 0.917 | | | 0.812 | | |
| **Cognitive engagement (SD = 0, SA = 10)** | | 0.936 | 0.785 | | 0.940 | 0.773 | | 0.942 | 0.797 |
| At work, my mind is focused on my job | 0.922 | | | 0.915 | | | 0.931 | | |
| At work, I focus a great deal of my attention on my job | 0.886 | | | 0.856 | | | 0.910 | | |
| At work, I am absorbed by my job | 0.782 | | | 0.840 | | | 0.733 | | |
| At work, I pay a lot of attention to my job | 0.909 | | | 0.889 | | | 0.925 | | |
| At work, I devote a lot of attention to my job | 0.924 | | | 0.894 | | | 0.946 | | |

**Table 10.4** Heterotrait-monotrait ratio (HTMT) for example application

| | Group | | | Males | | | Females | | |
|---|---|---|---|---|---|---|---|---|---|
| | Autonomy | Cognitive engagement | Skill discrepancy | Autonomy | Cognitive engagement | Skill discrepancy | Autonomy | Cognitive engagement | Skill discrepancy |
| Autonomy | | | | | | | | | |
| Cognitive engagement | 0.229 | | | 0.270 | | | 0.195 | | |
| Skill discrepancy | 0.341 | 0.403 | | 0.493 | 0.414 | | 0.182 | 0.423 | |

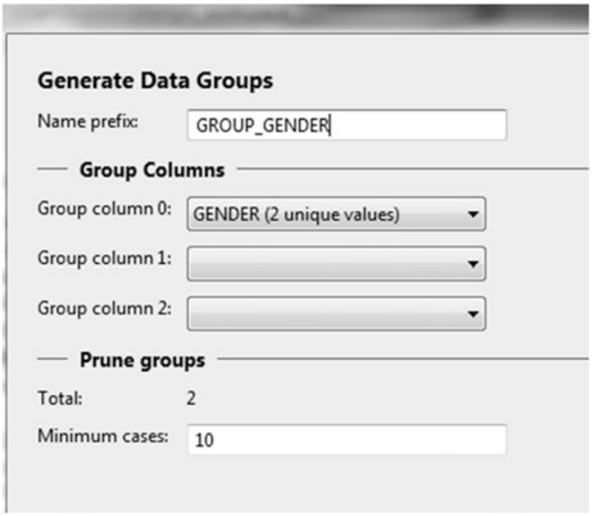


**Fig. 10.3** Assign initial name to group and selection of categorical variable

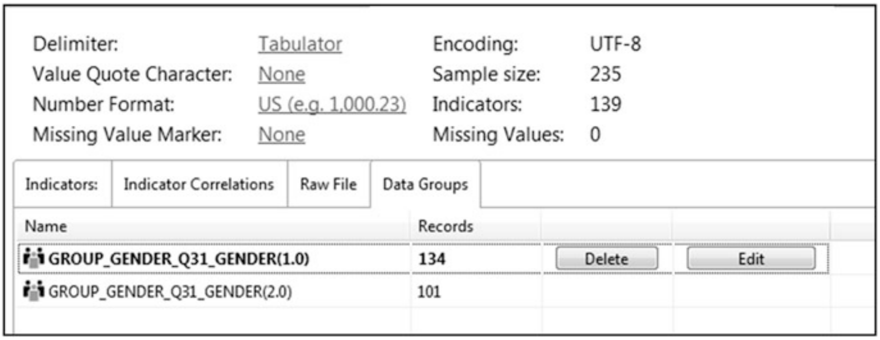


**Fig. 10.4** Subpopulations generated

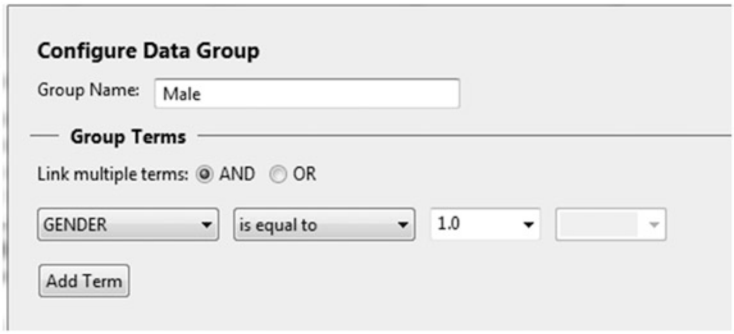


**Fig. 10.5** Subpopulation Group_GENDER_Q31_GENDER(1.0) is renamed to male

the following criteria: (a) identical indicators per measurement model, (b) identical data treatment, and (c) identical algorithm settings or optimization criteria (Henseler et al. 2016). All measurement indicators must be included in the constructs across all groups.

The execution of the MICOM procedure includes reviewing the process that was followed during the survey development. Specifically, this evaluation involves a further qualitative assessment of the items to ensure the constructs were initially designed as equivalent. For example, with international studies, translation and back translation practices should have been employed. Additionally, all the data must have been treated identically (e.g., dummy coding, reverse coding, or other forms of recoding, standardization, or missing value treatment). Outliers should also be identified and treated in a similar manner. The items loading on each construct must be invariant across groups as well. Finally, algorithm settings must be identical, and optimization criteria should be applied (Henseler et al. 2016). All of these guidelines are observed to ensure that a composite is a unidimensional entity with the same nomological net across all the groups (Henseler et al. 2016). If all of the above criteria have been met, which is the case for the present example, then configural invariance is established.

The objective of the second step of the MICOM procedure is to examine compositional invariance, which occurs when composite scores are created equally across groups (Dijkstra and Henseler 2011). Permutation tests are also conducted to statistically assess whether compositional invariance is present. Permutation tests are nonparametric (Henseler et al. 2016). For each permutation run, the correlations between the composite scores using the weights obtained from the first group are computed against the composite scores using the weights obtained from the second group (Henseler et al. 2016).

First, select calculate, then Permutation. Under Setup (see Fig. 10.6), specify the desired subpopulations for Group A and Group B. Permutations should be set at 5000. The test type option generally can remain at the two-tailed default as can the significance level of 0.05. But if the sample sizes are smaller and directional hypotheses are involved, a one-tailed test can be applied. Parallel Processing can also remain as the default. Under the Partial Least Squares tab, the Maximum Iterations should be set to 5000, and the Weighting Scheme should remain on Path. The Stop Criterion defaults to 7, but can be adjusted to another small number, such as 5. With regard to missing values, mean replacement is recommended when there are less than 5% of the values missing per indicator (Hair et al. 2014a). Casewise or listwise deletion removes all cases from the analysis that include missing values in any of the indicators used. This may result in a much lower dataset due to missing values. Pairwise deletion uses all observations that contain complete responses for the calculations within the model parameters. Therefore, based on the volume of missing data, select the appropriate setting. The default is set to Mean Replacement. All other defaults are appropriate (e.g., No Weighting Vector).

After the calculation, the output report will default to the Path Coefficients. Under the Quality Criteria options at the bottom of the screen, the desired output report is MICOM. Tabs are available in the MICOM results for the second and third steps.

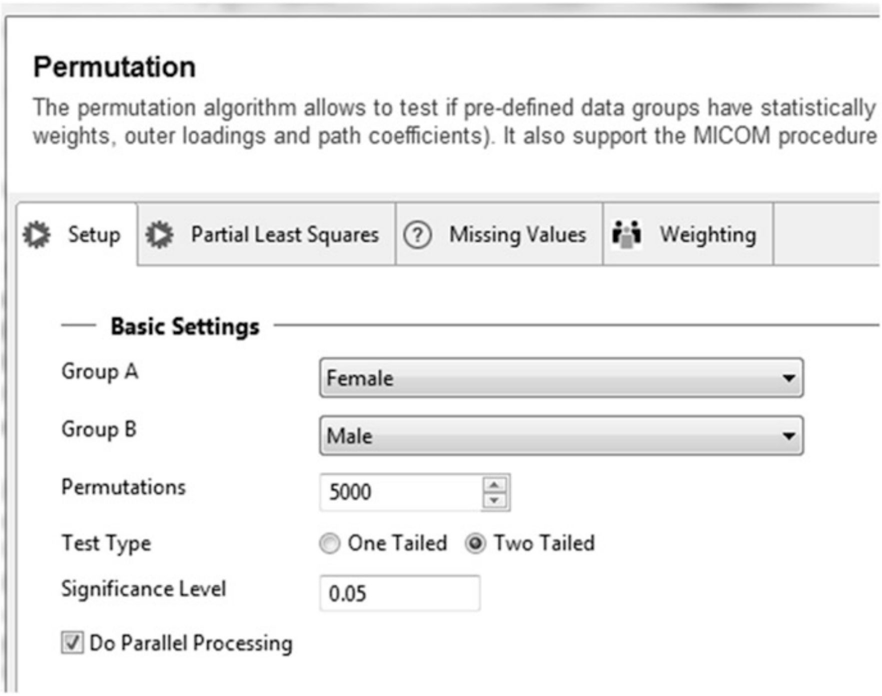


**Fig. 10.6** Setup for permutation

The MICOM permutation results report also includes the subsequent Step 3 portion of the MICOM procedure (Henseler et al. 2016).

We continue our example with the three-construct theoretical model that examines gender and salesperson roles. As shown in Table 10.5, the MICOM results report for the second step which indicates that compositional invariance has been demonstrated for all the constructs. This is evident based on the original correlations being equal to or greater than the 5.00% quantile correlations (shown in the 5% column).

A permutation test compares the composite scores of the first and second group to determine if the correlation $c$ is significantly different from the empirical distribution of $c_u$ (represented by the 5.00% quantile) (Henseler et al. 2016). If the results indicate that compositional invariance is a problem for one or more of the constructs, items can be deleted from the constructs in an effort to achieve invariance. Another much less desirable option is to remove entire constructs from the group-specific comparisons, provided that doing so is supported by theory (Henseler et al. 2016).

The next step is to evaluate the results tab for the third step of the MICOM procedure. Table 10.6 shows the first portion of the results. In this step, we assess the composites' (constructs) equality of mean values and variances across the groups. For invariance to be established, the first column (mean original difference) must

**Table 10.5** MICOM Step 2 results report

| | Original correlation | Correlation permutation mean | 5.00% | Permutation *p*-values |
|---|---|---|---|---|
| Autonomy | 0.99 | 0.995 | 0.987 | 0.093 |
| Cognitive engagement | 0.999 | 0.998 | 0.995 | 0.485 |
| Skill discrepancy | 0.999 | 0.998 | 0.994 | 0.722 |

**Table 10.6** MICOM Step 3 results report—part 1

| | Mean original difference (males − females) | Mean permutation mean difference (males − females) | 2.50% | 97.50% | Permutation *p*-values |
|---|---|---|---|---|---|
| Autonomy | 0.098 | −0.005 | −0.268 | 0.245 | 0.442 |
| Cognitive engagement | 0.117 | −0.006 | −0.253 | 0.26 | 0.4 |
| Skill discrepancy | −0.217 | 0.001 | −0.245 | 0.269 | 0.088 |

**Table 10.7** MICOM Step 3 results report—part 2

| | Variance original difference (males − females) | Variance permutation mean difference (males − females) | 2.50% | 97.50% | Permutation *p*-values |
|---|---|---|---|---|---|
| Autonomy | −0.207 | 0.011 | −0.378 | 0.398 | 0.242 |
| Cognitive engagement | **−0.544** | 0.014 | **−0.518** | **0.495** | 0.03 |
| Skill discrepancy | 0.187 | 0.002 | −0.581 | 0.586 | 0.569 |

be a number that falls within the 95% confidence interval. This is assessed by comparing the mean original difference to the lower (2.5%) and upper (97.5%) boundaries shown in columns three and four. If the mean original difference is a number that falls within the range of the lower and upper boundaries, then the first part of step three has been met, thus providing initial evidence of invariance. The constructs in Table 10.6 all pass this portion of the test for invariance.

The second portion of the results for the MICOM step three is shown in Table 10.7. Within SmartPLS, these results will appear to the right of the output presented in Table 10.6. Additionally, for illustration purposes, the construct titles have been displayed again with the output for this second assessment. Similar to the assessment conducted using Table 10.6, the data in column one (variance original difference) must be a number that falls within the 95% confidence interval. Therefore, the first column is again compared to the lower (2.5%) and upper (97.5%) confidence interval. In order to conclude full measurement invariance for the composites (Henseler et al. 2016), all the constructs must fall within the 95% confidence interval. However, in Table 10.7, note that the variance original difference value for the construct cognitive engagement does not fall within the

95% confidence interval. The first portion of Step 3 (Table 10.6) indicated partial invariance for cognitive engagement. But the construct did not meet the guidelines in this step for establishing full invariance. Therefore, only partial invariance is confirmed for this construct. Partial invariance is present when a construct passes only one of the two confidence interval tests, as illustrated with the example shown in Tables 10.6 and 10.7. The permutation *p*-values greater than 0.05 in Table 10.6 provide additional support for the cognitive engagement construct passing the measurement invariance test.

By establishing full measurement invariance, the composites (measurement models) of the two groups can be analyzed using the pooled data. However, using such pooled data without first establishing full measurement invariance could be misleading if there are differences in the structural model that have not been accounted for (Henseler et al. 2016).

If a construct does not pass the third MICOM step (e.g., had cognitive engagement failed both tests in Tables 10.6 and 10.7), and there is a significant difference in the composites' equality of mean values and variances across groups, then that construct should be removed from the analysis. Another possibility, however, is the group differences in the structural model can be accounted for by using the non-invariant construct as a moderator (e.g., cognitive engagement could be the moderator) (Henseler et al. 2016). This would be similar to using gender as the moderator. That is, since we know there are differences in the measurement for the construct, it could be used as the categorical variable of interest. For example, respondents with high cognitive engagement could be compared to those with low cognitive engagement. Using a mean or median split to divide the respondents into high and low groups is not a good approach since the division into groups is arbitrary and non-theoretical. Rather, a better methodology is to apply a cluster analysis to the variable/construct to identify high and low groups (Hair et al. 2016a).

### *10.3.3 Step 3: Analyze and Interpret Permutation Results*

Once invariance is established, the focus is to determine if the path coefficients of the theoretical models for the two groups are significantly different. We will first begin by analyzing the group separately prior to determining if there are group-specific differences. In order to run each group separately, a data file containing only the male participants and another containing only the female participants is needed. For this example, those files were generated in SPSS, converted to .csv files, and imported into my current project. Therefore, this project in SmartPLS contains one model and three data files. Using the guidelines set out for evaluation of a measurement model (Hair et al. 2014a), run the model for each group separately. As noted in Table 10.8, the relationship between autonomy and skill discrepancy is significant for males ($p$-value = 0.00) and is not for females ($p$-value = 0.222). The other relationships, autonomy and cognitive engagement as well as skill discrepancy and cognitive engagement, do not indicate a major difference between males and

**Table 10.8** Bootstrapping results for males and females separately

| | Males | | | | | Females | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | *p*-values | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | *p*-values |
| Autonomy → cognitive engagement | 0.116 | 0.118 | 0.099 | 1.172 | 0.241 | 0.151 | 0.144 | 0.132 | 1.144 | 0.253 |
| Autonomy → skill discrepancy | 0.471 | 0.485 | 0.072 | 6.548 | 0 | 0.171 | 0.209 | 0.14 | 1.221 | 0.222 |
| Skill discrepancy → cognitive engagement | 0.334 | 0.339 | 0.098 | 3.396 | 0.001 | 0.36 | 0.393 | 0.143 | 2.514 | 0.012 |

females. Next, it is necessary to determine if the difference between the two groups is significant. This can be accomplished by returning to the output for the permutation test.

The permutation test results were obtained as a part of testing for measurement invariance. As you may recall, when running the permutation test, the output reports were set to default on the path coefficient output. If you again review the permutation output reports, you will note that the initial column under the path coefficient results (see Table 10.9) displays the hypothesized structural relationships. The next two columns show the original path coefficients for the groups of interest, in this example, males and females. The following two columns indicate the path coefficient original differences as well as the permutation mean differences, which are followed by the lower and upper boundaries for the 95% confidence interval. The final column contains the permutation *p*-Value. A permutation *p*-value of less than or equal to 0.10 designates a significant difference between the two groups of interest. The relationship between autonomy and skill discrepancy indicates a significant difference between males and females. This is evident by the permutation *p*-value of 0.04 in Table 10.9.

Using the information from the group-specific bootstrapping as well as the above permutation test, we can now indicate that there is a significant difference between male and female salespeople as it relates to autonomy and skill discrepancy. This is important for sales managers to understand. Specifically, the findings reveal that male and female salespeople operate differently in their roles as salespersons. For example, there is a significant relationship between autonomy and skill discrepancy for male salespersons, as well as a significant relationship between skill discrepancy and cognitive engagement. Therefore, skill discrepancy partially mediates the relationship between autonomy and cognitive engagement. Since sales managers want their sales force to be cognitively engaged in the sales process, these findings indicate that for males, autonomy is indirectly related to sales engagement, as well as being directly related. In contrast, the link between autonomy and skill discrepancy is not significant for females, indicating that skill discrepancy does not mediate the relationship between autonomy and cognitive engagement. Therefore, additional research is needed to identify alternative antecedents for female salespersons that will lead to stronger cognitive engagement in their sales roles.

MGA allows researchers to determine significant differences among observed characteristics such as age, gender, or country of origin. While the path coefficients for the partitioned groups will almost always indicate numerical differences, understanding when those differences are significant is the role that MGA plays. These differences may not be evident in aggregate data since significant positive and negative group-specific results may offset one another.

**Table 10.9** Permutation test path coefficient results

| | Path coefficients original (males) | Path coefficients original (females) | Path coefficients original difference (males − females) | Path coefficients permutation mean difference (males − females) | 2.50% | 97.50% | Permutation *p*-values |
|---|---|---|---|---|---|---|---|
| Autonomy → cognitive engagement | 0.116 | 0.151 | −0.035 | 0.004 | −0.315 | 0.339 | 0.825 |
| Autonomy → skill discrepancy | 0.471 | 0.171 | 0.3 | −0.009 | −0.291 | 0.283 | 0.04 |
| Skill discrepancy → cognitive engagement | 0.334 | 0.36 | −0.026 | −0.007 | −0.347 | 0.347 | 0.961 |

## 10.4 Summary

Virtually, all previous social sciences research focused on understanding a single sample of data. Researchers examined the total sample, without considering subsamples, primarily because they assumed this approach provided an accurate understanding of the findings. They also analyzed the total sample findings because there were limited scientific, rigorous analytical procedures to divide the sample into meaningful subgroups. The most widely applied approach was to use theoretical a priori-defined simple approaches, such as size of firms, age, gender, or income. While helpful, subgroup analyses based on a priori-defined groups often did not assess measurement characteristics and were typically limited to attempting to understand a single relationship or model parameter. What was lacking was a simple, straightforward, efficient method for examining multiple relationships/parameters simultaneously and efficiently. The PLS-MGA, particularly in combination with assessing invariance, represents considerable progress in filling this void for researchers that are using PLS-SEM.

PLS-MGA substantially improves the ability of researchers to identify meaningful and significant differences in multiple relationships across group-specific results (Picon-Berjoyo et al. 2016; Sarstedt et al. 2014; Schlagel and Sarstedt 2016). Specifically, multiple model parameters can be examined simultaneously, and if statistically significant differences are present in the theoretical model, they can be efficiently identified. Moreover, in combination with the MICOM procedure, researcher can add an additional level of accuracy to their findings by including an assessment of the measurement characteristics of their constructs. Since research that does not examine group-specific differences often leads to misinterpretation of the results (Hult et al. 2008), it is important for researchers to apply this procedure when meaningful subgroups are present in the data or when they are subsequently identified using methods for assessing unobserved heterogeneity in sample data.

A primary concern of social science researchers, when comparing path coefficients among groups, should be to confirm that the construct measures are equivalent across the groups. Therefore, testing for measurement invariance is necessary to avoid introducing bias into research findings (Hair et al. 2014a; Henseler et al. 2016). MGA can be easily executed by following the approach provided in this chapter (Fig. 10.1): Step 1, Generate Data Groups; Step 2, Test for Invariance; and Step 3, Analyze and Interpret Results. By observing and following the guidelines, predefined data groups can be examined using PLS path modeling, and if meaningful and significant differences are present in the data, they can be reported and explained (Hair et al. 2014a, 2017b; Lohmöller 1989), therefore improving the rigor of research publication practices (Hair et al. 2012a, b, 2013, 2014b; Sarstedt and Mooi 2014) and improving our understanding of previously misunderstood theoretical relationships.

This study focused on differences between two groups; however, there are times when more than two groups are involved. Future research should provide step-by-step instructions on comparing more than two groups. Additionally, this study explained the permutation procedure for conducting MGA. Since there are several means of conducting MGA, future research is needed that compares the various methods of MGA to better understand the differences in the results of each. Similarly, since the introduction of consistent PLS (PLSc) (Dijkstra and Henseler 2015), MGA has yet to be combined with that process to determine the proper use of traditional bootstrapping and consistent bootstrapping. Finally, the guidelines provided for conducting a MGA with PLS-SEM include the MICOM test for invariance; future research should explore the possibility of simplifying the process allowing for simultaneous assessment of configural and compositional invariance. Finally, due to the controversy over minimum sample size, the establishment of a procedure to test for a lack of statistical power due to sample size is encouraged.

Beyond the analysis conducted in this chapter based on a priori knowledge, researchers should also conduct an analysis to examine potential differences that may not have been identified via a priori-defined categorical variables. That is, unobserved heterogeneity should be examined (Hair et al. 2016b; Jedidi et al. 1997; Matthews et al. 2016; Sarstedt et al. 2018). Both MGA and tests to uncover unobserved heterogeneity can be used to identify differences among subpopulations within a larger dataset. MGA, however, uses categorical variables that have been identified a priori and collected in the dataset. However, sources of such differences can be difficult to identify; therefore, recent methods such as PLS-GAS, PLS-POS, and PLS-IRRS can be instrumental for uncovering other areas that partition data into groups (Hair et al. 2014a). In an effort to improve the validity of PLS-SEM results, which continue to be enhanced (Hair et al. 2017a), researchers are encouraging the routine application of such techniques (Hair et al. 2011, 2012c, 2013; Wilson et al. 2014).

**Acknowledgments** This chapter refers to the use of the statistical software SmartPLS (http://www.smartpls.com) (Ringle et al. 2015).

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