CHAPTER 5
DATA ANALYSIS AND DISCUSSION
5. Data Analysis and Discussion

This chapter is organized as follows: Section 5.1 provides the descriptive statistics of the respondents. Sections 5.1 and 5.2 give explanation of the measurement model and structural model, respectively, using the Partial Least Square Structural Equation Modelling (PLS-SEM). Section 5.3 provides the analysis of the mediation effect of supply chain integration (SCI) and supply chain agility (SCA). Section 5.4 presents the impact-performance matrix analysis, which provides insights into the possible areas of improvements to the Indian manufacturers.

5.1 Descriptive Statistics

As described earlier, Indian manufacturing firms were selected as respondents. Figures 5.1-5.7 show the descriptive statistics of the 122 respondents in our sample.

Figure 5.1 shows that our sample had >10 different manufacturing sectors. Most of the respondents are from the electronics manufacturing sector, followed by some from the automotive and computer equipment manufacturing sector. Figure 5.2 gives the designation wise distribution of the respondents. As explained in the previous chapter, respondents were chosen based on their knowledge about firm suppliers and customers. Therefore, 95% of the respondents belonged to the managerial and executive cadre. Sixty-nine percent of the respondents had work experience of >5 years as shown in Figure 5.3. The educational level of the respondents is given in figure 5.4. It is evident that almost all the respondents (97%) have completed graduation and above. In terms of gender distribution of the respondents, figure 5.5 evinces that 89% of the respondents are male and 11% are female.
Employee strength of the sample organization is as shown in figure 5.6. Eighty-five percent of the organizations had an employee strength of >100. Finally, the age of the organization is shown in figure 5.7. It is evident that 66% of the organizations in the sample functioned for ≥5 years.

Figure 5.1 Industry-wise Distribution
Figure 5.2 Designation-wise Distribution

Figure 5.3 Work Experience of the Respondents
Figure 5.4 Educational Details of the Respondents

Figure 5.5 Gender-wise Distribution of the Respondents
Figure 5.6 Number of Employees

Figure 5.7 Age of the Organization
5.2 PLS-SEM Model Assessment

One of the challenges in survey research is the selection of an appropriate statistical model for analysis. Partial Least Squares based Structural Equation Modelling (PLS-SEM) and Covariance-Based Structural Equation Modelling (CB-SEM) modelling are two well-known multivariate data analysis methods for researchers and scholars (e.g. Bagozzi & Yi, 1988; Götz, Liehr-Gobbers, & Krafft, 2010; Lowry & Gaskin, 2014).

CB-SEM is based on the concept of factor analysis, which is suitable for theory testing. It uses maximum likelihood estimation, whereas PLS-SEM is based on the principal component concept (which is suitable for theory building) and uses the partial least squares estimator (Hair, Ringle, & Sarsted, 2011; Lowry & Gaskin, 2014; Vinzi, Chin, Henseler, & Wang, 2010). Partial least squares, variance-based SEM is widely accepted in business management research, including in operations management (Carter, Sander, & Dong, 2008; Peng & Lai, 2012; Shah & Goldstein, 2006); information systems management (Urbach & Ahlemann, 2010); marketing management (Hair, Sarstedt, Ringle, & Mena, 2012) and organizational behaviour and human resource management (Anderson & Gerbing, 1988). We have opted for PLS-SEM in our study for the following reasons: 1) It is suitable for theory building studies (Vinzi et al., 2010; Sarsted, 2008). 2) It is considered appropriate for examining complex cause-effect-relationship models (Henseler, Ringle, & Sinkovics, 2009; Lowry & Gaskin, 2014). 3) It is a non-parametric approach, and it poses fewer restrictions especially on data distribution and sample size (Vinzi et al., 2010).

To test our hypothesis, we used smartPLS 3 software (Ringle et al., 2014). We used the PLS-SEM approach and assessed the measurement model (also referred to as the
outer model) and structural model (also referred to as the inner model). Figure 5.8 provides more details of our approach.
Figure 5.8 Conceptual Model
5.2.1 Measurement Model Assessment

In PLS-SEM, assessment of the measurement model (also referred to as the outer model) includes composite reliability (CR) to evaluate internal consistency, individual indicator reliability and average variance extracted (AVE) to evaluate convergent validity (Hair, Hult, Ringle, & Sarstedt, 2013, p.100).

5.2.1.1 Internal Consistency Reliability

This is a form of reliability that is used to access the consistency of results across items of the same variables (Hair et al., 2013). It determines whether the items measuring a variable are similar in their scores (Hair, Tatham, Anderson, & Black, 2006). Internal consistency reliability is accessed by using CR. Table 5.1 shows the CR values of all the latent variables used in this study. These values were found to be > 0.70 (Hair et al., 2006) which establishes internal consistency.

5.2.1.2 Convergent Validity

This refers to the extent to which a measure correlates positively with alternative measures of the same variable (Hair et al., 2013, p. 115). AVE was calculated to access convergent validity. Table 5.1 shows the AVE values of all the latent variables used in this study. These values were found to be more than the prescribed value of 0.50 (Hair et al., 2006) and therefore establish convergent validity.

5.2.1.3 Discriminant Validity

This is the extent to which a variable is truly distinct from other variables, in terms of how much it correlates with other variables, and how much indicators represent only a single variable (Hair et al., 2013, p. 115). The criterion and cross-loading scores of Fornell & Larcker (1981) were used to establish discriminant validity. Table 5.1
demonstrates that the square root of AVE for all latent variables was higher than the inter-construct correlations (Fornell & Larcker, 1981) and therefore they confirm discriminant validity. Further, all indicators’ individual loadings were found to be higher than their respective cross-loadings (Hair et al., 2013). This provides additional evidence for discriminant validity (Appendix E).
Table 5.1: Construct Validity and Discriminant Validity – Fornell and Lacker Criterion

<table>
<thead>
<tr>
<th>Latent Variables</th>
<th>AVE</th>
<th>CR</th>
<th>BNV</th>
<th>CMT</th>
<th>CN</th>
<th>CRD</th>
<th>OC</th>
<th>SCA</th>
<th>SCI</th>
<th>SCO</th>
<th>SCP</th>
<th>TMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNV</td>
<td>0.511</td>
<td>0.805</td>
<td>0.715</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CMT</td>
<td>0.874</td>
<td>0.933</td>
<td>0.204</td>
<td>0.935</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CN</td>
<td>0.559</td>
<td>0.701</td>
<td>0.673</td>
<td>0.324</td>
<td>0.748</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRD</td>
<td>0.54</td>
<td>0.823</td>
<td>0.398</td>
<td>0.192</td>
<td>0.335</td>
<td>0.735</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OC</td>
<td>0.716</td>
<td>0.835</td>
<td>0.325</td>
<td>0.377</td>
<td>0.349</td>
<td>0.31</td>
<td>0.846</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCA</td>
<td>0.584</td>
<td>0.864</td>
<td>0.418</td>
<td>0.263</td>
<td>0.381</td>
<td>0.295</td>
<td>0.465</td>
<td>0.764</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCI</td>
<td>0.598</td>
<td>0.881</td>
<td>0.429</td>
<td>0.165</td>
<td>0.397</td>
<td>0.256</td>
<td>0.332</td>
<td>0.516</td>
<td>0.773</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCO</td>
<td>NA</td>
<td>0.87</td>
<td>0.838</td>
<td>0.465</td>
<td>0.798</td>
<td>0.662</td>
<td>0.575</td>
<td>0.512</td>
<td>0.461</td>
<td>0.529</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCP</td>
<td>0.522</td>
<td>0.845</td>
<td>0.392</td>
<td>0.24</td>
<td>0.362</td>
<td>0.263</td>
<td>0.451</td>
<td>0.677</td>
<td>0.667</td>
<td>0.466</td>
<td>0.723</td>
<td></td>
</tr>
<tr>
<td>TMS</td>
<td>0.554</td>
<td>0.832</td>
<td>0.549</td>
<td>0.14</td>
<td>0.507</td>
<td>0.368</td>
<td>0.19</td>
<td>0.284</td>
<td>0.259</td>
<td>0.715</td>
<td>0.206</td>
<td>0.744</td>
</tr>
</tbody>
</table>

Notes: AVE: Average Variance Extracted; CR: Composite Reliability

*aThe off-diagonal values are the correlations between latent variables and the diagonal are the square root of AVE.*
5.2.1.4 Indicator Reliability

This represents how much of the variation in an item is explained by a variable (Hair et al., 2013). Indicator reliability was assessed using the outer loadings as shown in Appendix D. A higher outer loading on a variable indicates that the associated measure has much in common, that is measured by the variable (Hair et al., 2013). Hair, Hult, Ringle, & Sarstedt (2013) suggested that items having a loading >0.70 should be retained, items having an outer loading value >0.40 should be omitted and that its impact on the AVE and CR of the variable should be analysed. If the AVE and CR of the variable reach above the threshold value, then the given item should be omitted; otherwise, it should be retained. Two reflective measures from sub constructs of SCO, SCA and SCP, along with one reflective indicator from SCI were omitted (refer appendix B). Omitting these items resulted in an increase in CR and AVE above the suggested threshold values of 0.70 and 0.50, respectively (Hair et al., 2013, p. 100). We next provide the assessment of our structural model.

5.2.2 Structural Model Assessment

After establishing the reliability and validity of the latent variables in the measurement model, we assess the structural model (also referred to as the inner model) to test the relationship between endogenous and exogenous variables. In PLS-SEM, structural model assessment includes path coefficients to evaluate the significance and relevance of structural model relationships, R² value to evaluate the model’s predictive accuracy, Q² to evaluate the model’s predictive relevance and f² to evaluate the substantial impact of the exogenous variable on an endogenous variable (Hair et al., 2013).
5.2.2.1 Path-Coefficients

Figures 5.9 and 5.10 shows the path coefficient for the direct relationship between SCO and other three constructs. Nonparametric bootstrapping routine advocated by Vinzi et al., (2010), has been used on 122 data points and 5000 samples. “Bootstrapping is a re-sampling approach that draws random samples (with replacements) from the data and uses these samples to estimate the path model multiple times under slightly changed data constellations” (Hair et al., 2013, p. 162). The main purpose of bootstrapping is to calculate the standard error of coefficient estimates in order to examine the coefficient’s statistical significance (Vinzi et al., 2010).

5.2.2.2 Discussions

SCO was positively associated with SCP, SCI and SCA, which supports H1, H2 and H4 (figure 5.9). Hence, it is very important for supply chain members to embrace SCO and practice it, because SCO has a direct and positive impact on SCP, SCI and SCA. Because SCI, SCA and even SCP are not standalone activities and call for the joint efforts of supply chain members, SCO becomes crucial for aligning all efforts.

SCI and SCA both positively influence the SCP-supporting hypothesis H3 and H6 (Figure 5.10). Because the nature of the supply chain is complex, it is crucial that players collaborate to enhance the performance of the entire system. Our results are consistent with those of Flynn, Huo, & Zhao (2010) and Prajogo & Olhager (2012), who established a positive relationship with SCI and SCP. As far as agility is concerned, the survival of the fittest rule is true in results, too. It requires the joint ability of all the supply chain members to change quickly to beat the competition and improve SCP. These findings were similar to those of Blome, Schoenherr, &
Rexhausen (2013). The path coefficient value of the SCA-SCP relationship is slightly lower than that of the SCI-SCP path. This indicates that manufacturers place more emphasis on SCI than on SCA while considering SCM.

Figure 5.9 PLS-SEM Output for the Direct Relationship Between SCO and SCP, SCA and SCI
Figure 5.10 PLS-SEM Output for the Direct Relationship Between SCI and SCP and that Between SCA and SCP

Table 5.2 Results of Hypothesis Testing and Structural Relationship

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path</th>
<th>Path Coefficient</th>
<th>Standard Error</th>
<th>t-Statistic</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>SCO -&gt; SCP</td>
<td>0.508</td>
<td>0.065</td>
<td>7.839*</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>SCO -&gt; SCI</td>
<td>0.513</td>
<td>0.077</td>
<td>6.697*</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>SCI -&gt; SCP</td>
<td>0.663</td>
<td>0.059</td>
<td>7.564*</td>
<td>Supported</td>
</tr>
<tr>
<td>H5</td>
<td>SCO -&gt; SCA</td>
<td>0.511</td>
<td>0.066</td>
<td>7.754*</td>
<td>Supported</td>
</tr>
<tr>
<td>H6</td>
<td>SCA -&gt; SCP</td>
<td>0.432</td>
<td>0.057</td>
<td>11.302*</td>
<td>Supported</td>
</tr>
</tbody>
</table>

*t-values for two tailed tests: *p < 0.01
5.2.2.3 Assessing $R^2$ Values

$R^2$ (Coefficient of determination) value is used to evaluate the structural model. This coefficient measures the predictive accuracy of the model and is calculated as the squared correlation between actual and predictive values of a specified endogenous construct. The $R^2$ values represent the exogenous variables’ combined effects on the endogenous latent variables and it also represents the amount of variance in the endogenous constructs explained by all of the exogenous constructs linked to it (Hair et al., 2013). In our study, the endogenous variables namely SCA, SCI and SCP have $R^2$ value 0.362, 0.216 and 0.520 respectively. This reflects the fact the structural model developed in this study has predictive relevance. Further the examination of the endogenous variables’ predictive power has moderate $R^2$ values (refer table 5.3).

<table>
<thead>
<tr>
<th>Endogenous Latent Variable</th>
<th>$R^2$</th>
<th>Adjusted $R^2$</th>
<th>$Q^2$</th>
<th>Effect Size$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCA</td>
<td>0.362</td>
<td>0.351</td>
<td>0.206</td>
<td>Medium</td>
</tr>
<tr>
<td>SCI</td>
<td>0.216</td>
<td>0.209</td>
<td>0.124</td>
<td>Small</td>
</tr>
<tr>
<td>SCP</td>
<td>0.520</td>
<td>0.488</td>
<td>0.458</td>
<td>Medium</td>
</tr>
</tbody>
</table>

Small: $0.0 < Q^2$ effect size $< 0.15$; Medium: $0.15 < Q^2$ effect size $< 0.35$; Large: $Q^2$ effect size $> 0.35$

5.2.2.4 Assessing $Q^2$ Values

Blindfolding was used to cross-validate the model’s predictive relevance for each of the individual endogenous variables, the Stone-Geisser $Q^2$ value (Geisser, 1974; Stone, 1974). By performing the blindfolding technique (Hair et al., 2013) with an omission distance of 7 yielded cross-validated redundancy $Q^2$ values of all the endogenous variables. In this study, SCA has a $Q^2$ value of 0.206; SCI has 0.124 and SCP has 0.458 respectively. This shows medium, small and large effect sizes,
respectively. Because all the $Q^2$ values are $>0$, it establishes the fact that the PLS structural model has predictive relevance.

5.2.2.4 Assessing $f^2$ Values

$f^2$ size effect is the measure to evaluate the change in $R^2$ value when a specified exogenous variable is omitted from the model. The size effect is calculated as:

Formula:

Where $R^2_{\text{included}}$ and $R^2_{\text{excluded}}$ are the $R^2$ values of endogenous latent variables when a selected exogenous variable is included or excluded from the model (Hair Jr et al., 2013). $f^2$ size effect shows the impact of a specific predictor latent variable on an specific endogenous variable as shown in table 5.6. In this study, $f^2$ size effect varies from small to large for all the exogenous variables in explaining the SCA, SCI and SCP.

Table 5.4 Results of $f^2$

<table>
<thead>
<tr>
<th>Endogenous Latent Variables</th>
<th>SCA</th>
<th>SCI</th>
<th>SCP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exogenous Latent Variables</td>
<td>Path Coefficients</td>
<td>$f^2$ size effect</td>
<td>Path Coefficients</td>
</tr>
<tr>
<td>SCO</td>
<td>0.511</td>
<td>0.146</td>
<td>0.513</td>
</tr>
<tr>
<td>SCA</td>
<td>Not Applicable</td>
<td>Not Applicable</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>SCI</td>
<td>0.358</td>
<td>0.157</td>
<td>Not Applicable</td>
</tr>
</tbody>
</table>

Small: $0.0 < f^2$ effect size $< 0.15$; Medium: $0.15 < f^2$ effect size $< 0.35$; Large: $f^2$ effect size $> 0.35$
5.3 Mediation Analysis

This is carried out to examine the casual relationship between an exogenous variable and an endogenous variable by the inclusion of a third explanatory mediator variable (Hair et al., 2013). In PLS-SEM, the bootstrapping approach is suitable for mediation analysis because bootstrapping makes no assumption about the sampling distribution of the statistics and can be applied to small sample sizes (Hair et al., 2013). To carry out the mediation analysis in PLS-SEM, the first step is to assess the direct effect (i.e. p. 13) of the exogenous variable on the endogenous variable, which should be significant if the mediator is not included. (Zhao, Lynch & Chen, 2010)

\[ P_{13} \]

\[ P_{12} \]

\[ P_{23} \]

**Figure 5.11: Mediation Analysis Using Bootstrapping Approach**

If the direct path is significant, next step is to include the mediator variable in the PLS path model and assess the significance of the indirect path (i.e. \( p_{12} \times p_{23} \)). The significance of each individual path \( p_{12} \) and \( p_{23} \) is a necessary requirement for this condition. The indirect path can be assessed after running the bootstrapping procedure and if the indirect effect is found significant then mediator absorbs some of the direct...
path (Refer figure 5.11). To assess how much of the direct path is absorbed, variation accounted for (VAF) is calculated as

\[
VAF = \frac{(p_{12} \times p_{23})}{(p_{13} + p_{12} \times p_{23})}.
\]

Based on the value of VAF, following conditions of mediation effect is given by Hair et al., (2013, p.224):

i) If $0 < VAF < 0.20$, then No Mediation.

ii) If $0.20 < VAF < 0.80$, then Partial Mediation.

iii) If $VAF > 0.80$, then Full Mediation.

In this study, mediation analysis was carried out to estimate the magnitude of indirect effect of mediating variable (SCI and SCA) on the relationship between exogenous variable (SCO) and endogenous variable (SCP).

From figure 5.12 and 5.13 it is clear that indicates that SCI and SCA fully mediate the relationship between SCO and SCP. These results did not vary after controlling for age and size of the firms. A VAF value indicates that more than 80% of the total effect of an exogenous variable (SCO) on to SCP is explained by indirect effect (Table 5.6 and 5.7). Therefore, the effect of SCO on SCP is fully mediated through SCI and SCA. Therefore the supply chain players need to increase the level of integration and agility of the supply chains to enhance the total SCP, supporting the H4 and H7.

Finally, the combined effect of SCI and SCA together on SCO-SCP relationship is as shown in figure 5.14. We have already got support for SCI as mediator and SCA as mediator so it was evident that SCI and SCA will fully mediate the relationship
between SCO and SCP, supporting the H8. Therefore supply chain players need to collaborate and at the same time be agile in order to increase the SCP.

Figure 5.12 SCA as a Mediator
Figure 5.13 SCI as a Mediator
Table 5.5 Mediation Analysis: SCA as Mediator

<table>
<thead>
<tr>
<th>Exogenous Variables</th>
<th>Direct Effect</th>
<th>Indirect Effect</th>
<th>Total Effect</th>
<th>VAF Range</th>
<th>Mediation</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCO</td>
<td>0.08</td>
<td>0.4331</td>
<td>0.5131</td>
<td>0.8440</td>
<td>Full</td>
</tr>
</tbody>
</table>

Mediating Variable: SCA; Endogenous Variable: SCP

Table 5.6 Mediation Analysis: SCI as Mediator

<table>
<thead>
<tr>
<th>Exogenous Variables</th>
<th>Direct Effect</th>
<th>Indirect Effect</th>
<th>Total Effect</th>
<th>VAF</th>
<th>Mediation</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCO</td>
<td>0.002</td>
<td>0.4104</td>
<td>0.4124</td>
<td>0.9951</td>
<td>Full</td>
</tr>
</tbody>
</table>

Mediating Variable: SCI ; Endogenous Variable: SCP

Table 5.7 SCI and SCA as Mediators

<table>
<thead>
<tr>
<th>Exogenous Variables</th>
<th>Direct Effect</th>
<th>Indirect Effect</th>
<th>Total Effect</th>
<th>VAF</th>
<th>Mediation</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCO</td>
<td>0.083</td>
<td>0.5482</td>
<td>0.6312</td>
<td>0.8685</td>
<td>Full</td>
</tr>
</tbody>
</table>

Mediating Variable: SCI ; Endogenous Variable: SCP
Figure 5.14: PLS Output After Bootstrapping
This section analysed and discussed mediation analysis in detail; the next section will describe impact performance matrix analysis (IPMA).

5.4 Impact Performance Matrix Analysis (IPMA)

Further investigation was carried out to analyse the relative priority of SCO dimensions on SCP. The IPMA (Hock, Ringle, & Sarstedt, 2010; Rigdon, Ringle, Sarstedt, & Gudergan, 2011) was carried out using smartPLS 3 software by taking the performance of each exogenous latent variable into account. IPMA results in a priority map for management-oriented presentations. For assigning priorities to different areas of management activities for their improvement for a particular endogenous latent variables’ performance level in the future, actions should have a relatively high impact (i.e. high path coefficient) and a relatively low performance (Hair et al., 2013).

Table 5.8 shows the impact and performance of each exogenous variable towards SCP the endogenous variable. Figure 5.15 shows that supply chain players should focus on the following SCO dimensions in the descending order of priority, considering the impact and performance: SCI, SCA, benevolence, credibility and top management support.

SCI scores high on both dimensions, that is, impact and performance. So, supply chain players need to collaborate to improve SCP. Our results are consistent with those of previous studies that highlight how SCI enhances SCP by reducing the bullwhip effect, avoiding duplication of activities, information symmetry, etc. Technology can be very useful for integrating supply chain players. SCA is the second dimension to be considered for improving SCP. Supply chain players should ensure that there is a high level of awareness regarding the business environment,
information among partnering firms is transferred in real time, member firms are empowered to take tough decisions, and that the capacity to adjust according to situations is high. Benevolence, credibility, and top management support are the next three dimensions to be focused upon. Benevolence and credibility together form trust. Trust is essential in all relationships and in the context of supply chains its importance is Paramount. Without trust, neither SCI nor SCA can be achieved, so enhancing SCP is out of the question. Therefore, supply chain managers do their best to improve the trust factor of the entire supply chain. The last on the list is top management support, which is crucial for the organization. All the factors that we have discussed, namely, benevolence, credibility, SCI, SCA and commitment, are the output of actions taken by the top management. The top management has the capability to head the organization, and without their support nothing can be achieved. Therefore, supply chain managers must convince the top management that supply chain management is an important business activity and requires the maximum support of the top management.
In this chapter, we described the sample characteristics of respondents. PLS-SEM was analysed using smartPLS 3, and we discussed and provided the interpretation of our
results. Further, post hoc analysis, including prediction analysis, and impact performance matrix analysis were carried out to generate greater insights. In the next chapter, we conclude the study with managerial implications and recommendations, limitations and future research scope.