CHAPTER 5

RESEARCH FINDINGS: STRUCTURAL EQUATION MODELLING

5.0 INTRODUCTION

This chapter discusses the outcome of the Structural Equation Modelling analysis utilised in this study with the ultimate objective being to confirm the hypothesised model. Initially, the chapter examines the conformity of the data and constructs in meeting structural equation modelling (SEM) assumptions. This is followed by the discussion on the measurement model which includes the analysis of validity and reliability. Before moving on to the structural model, mediation analysis is performed to check the significance of the relationships and the direct and indirect effects between the constructs in this study. Then, discussion on the structural model is presented and goodness of fit of the hypothesised model is examined. Finally, the chapter provides an analysis of the hypothesised relationships.

5.1 EXAMINATION OF THE SATISFACTION OF SEM ASSUMPTIONS

In structural equation modelling, data must fulfil the requirement of sample size, normality, and absence of multicollinearity problems (Kline, 1998). After measures of each construct have been verified and clarified through factor and reliability analysis, data need to be examined to ensure that they do not violate any of the assumptions of SEM that must be satisfied in order to proceed with the full model SEM analysis.

5.1.1 Sample Size

In SEM, sample size requirement depends on the level of complexity of the model and the types of estimation method used in the study (Hair et al., 1998). Since the Maximum Likelihood Method (ML) of estimation is used in SEM, it requires multivariate normally distributed continuous variables. To meet the assumption of normality, a generally accepted ratio to minimise the possibility of deviations from normality, is 15 respondents for each estimated parameter (Hair, Black, Babin, Anderson & Tatham, 2006), while the minimum is 5:1 between subject and parameter (Bentler & Chow, 1987). The lower bound of sample size as proposed by Kline (1998) should be at least 200. Determining the appropriateness of sample size is important because the accuracy and stability of SEM results decline as the number in the sample decreases and as the number of variables increases (Hair et al., 2006; Nachtigall et al., 2003).

In this study, the sample size was 208, which was slightly higher than the lower bound as proposed by Kline (1998). The proposed structural model consisted of six latent variables and 20 observed variables. For three latent variables, the item parcelling procedure was utilised to achieve the recommended ratio of sample size, besides fulfilling the requirement for answering the research questions proposed in this study.

5.1.1.1 Item Parcelling Procedure

The item parcelling procedure is commonly-used in SEM studies (Bandalos & Finney, 2001), the main purpose being to improve the variable to sample size ratio. Bagozzi and Edwards (1998) suggested that the use of parcelling reduces the number of parameter estimations and this will inadvertently fulfil the requirement of sample size ratio, as well as stabilising the parameter estimates. Researchers have also argued that the item parcelling procedure makes data conform to the assumption of normality as required in SEM estimation. Furthermore, this technique is believed to simplify a complex model while maintaining the concept of multiple indicator measurement (Garver & Mentzer, 1999).

The process involves aggregation of several items so as to achieve three to four indicators per factor. However, it should be noted that the construction of parcels must be done according to these guidelines:

i. items must be valid individual measures of the construct
ii. the level of specificity must be the same within and across parcels
iii. items that represent the parcel must fulfil the requirement of unidimensionality.

The average of the items will partially represent the observed variable under study.

Table 5.1
Aggregated Items to Form Scale Indicators

Observed variable	Indicators	Items
Prospector strategic orientation	Innovative	A7, A10, A15, A18
	Product Competitive	A1, A4, A8, A12
	Aggressive	A9, A11, A13, A14
	First-mover	A5, A17
Explorative learning	Experimentation	C3, C4, C8, C9, C13, C18
	Acquisition	C1, C2, C6, C17
Performance	Financial	D2, D3, D4, D5
	Product Innovation	D7, D9, D14
	Process Innovation	D11, D12

In this study, the parcelling procedure was used to achieve a more parsimonious estimation. Table 5.1 shows the indicators that were aggregated to form a parcel. Following the partial aggregation procedure recommended by Bagozzi and Heatherton (1994), items that represented each dimension were individually aggregated to represent each observed variable. This procedure allows us to reduce the number of variables and therefore, reduce the sample-parameter ratio. However, before combining these items, reliability and validity tests were performed to ensure unidimensionality of items in each parcel. Items with low and insignificant factor loadings, items that were highly correlated with other items, or cross-loaded into other variables, were omitted from the measures. This step is necessary since this procedure can only be conducted within a set of unidimensional items in order to avoid distortion of the factor structure of the data (West, Finch & Curran, 1995). After the reliability and validity measures had been met, item parcelling was performed to fulfil the sample-parameter ratio requirement in SEM.

5.1.2 Normality, Linearity and Homoscedasticity

Normality, which is one of the fundamental assumptions in multivariate analysis, refers to the shape of data distribution of a single metric variable (Hair et al., 1998). In order to check conformity of the data to this assumption, both graphical and statistical analyses were performed. The purpose of analysing the normal probability plot on each variable was to visually detect skewness and kurtosis. This will be further confirmed by comparing the statistical values of skewness and kurtosis to the threshold of +-2.58 (at 0.01 probability level).

Examination of the normal probability plot indicated normal distribution (Appendix 2) and this was further confirmed by the results of kurtosis and skewness as shown in Table 5.2. The value of skewness and kurtosis for each variable was within the recommended cut-off point with the highest value of kurtosis of 1.826 and skewness of 1.003.

Table 5.2
Mean, Standard Deviations, Skewness and Kurtosis

Observed variable	Mean	Std. deviation	Skewness	Kurtosis
Innovative	3.411	1.035	0.176	-0.427
Product Competitive	3.281	1.153	0.019	-0.673
Aggressive	3.855	0.956	-0.195	-0.018
First-mover	3.501	1.198	0.003	-0.432
System capabilities	3.487	0.943	-0.152	-0.321
Coordination capabilities	4.390	0.751	-0.755	1.190
Socialisation capabilities	4.919	0.690	-1.003	1.826
Experimentation	4.215	0.787	-0.569	0.600
Information Acquisition	3.535	0.883	0.016	-0.021
Financial	3.412	0.752	-0.289	-0.474
Product Innovation	3.444	0.665	-0.165	0.145
Process Innovation	3.529	0.707	-0.269	-0.308

Although univariate normality could be accessed through visual inspection of the normal probability plot, and the statistical result on kurtosis and skewness, it should be noted however, that univariate normality is not indicative of multivariate normality (Hair et al., 1998). Therefore, to confirm multivariate normality, visual examination of residual scatter plots is required, which not only provides an assessment of normality, but also gives an indication of linearity and homoscedasticity (Tabachnick & Fidell, 2001). The inspection of scatter plots in multiple regression analysis revealed straight line approximation indicating the existence of multivariate normality.

As for homoscedasticity, visual examination of the scatter plot involving studentised residuals and dependent variables as suggested by Hair et al. (1998), was employed to detect the existence of unequal variances. In this study, no discernible patterns of increasing or decreasing residuals were found and this indicated that the assumption of homoscedasticity holds.

5.1.3 Multicollinearity

Another requirement in multivariate analysis is the absence of multicollinearity problems. Multicollinearity occurs when inter-correlations among variables are high, thereby signifying that two separate variables may be redundant in measuring a construct (Kline, 1998). This threat can be minimised by using mean-centred transformation to all variables involved in the study (Aiken & West, 1991).

5.1.3 Correlation Analysis

Correlation analysis can be used to detect bivariate multicollinearity by locating values that exceed 0.85 (Kline, 1998). From Table 5.3, it can be seen that there was no multicollinearity problem and the data were, therefore, acceptable for further analysis and interpretation.

Table 5.3
Correlation Results for Observed Variables

	INNV	PCOMPV	AGRSV	FMOVER	SYSTEM	CORDNTE	SOCIAL	EXPRMT	ACQST	FIN	PRDINV	PRCSINV
INNV	1											
PCOMPV	0.497**	1										
AGRSV	0.599**	0.555**	1									
FMOVER	0.438**	0.485**	0.441**	1								
SYSTEM	-0.273**	-0.161*	-0.388**	-0.158*	1							
CORDNTE	0.167*	0.194**	0.329**	0.176*	-0.330**	1						
SOCIAL	0.221**	0.075	0.289**	0.099	-0.252**	0.413**	1					
EXPRMT	0.311**	0.269**	0.488**	0.319**	-0.365**	0.503**	0.402**	1				
ACQST	0.466**	0.432**	0.549**	0.330**	-0.429**	0.320**	0.232**	0.486**	1			
FINANCIAL	0.157*	0.088	0.213**	0.136	-0.197**	0.230**	0.113	0.279**	0.203**	1		
PRDINV	0.327**	0.324**	0.343**	0.341**	-0.113	0.259**	0.179**	0.328**	0.287**	0.429**	1	
PRCSINV	0.126	0.127	0.197**	0.116	-0.084	0.238**	0.258**	0.292**	0.133	0.410**	0.297**	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

In addition to the correlation matrix, tolerance and VIF statistics were also used to detect the existence of multicollinearity at multivariate level. These statistics give an indication of how much the variability of a specified independent variable is not being explained by other independent variables in the model. The value of tolerance should not be less than 0.1 and VIF must be well below the cut-off point of 10 as recommended by Neter, Wasserman and Kutner (1990). In Table 5.4, it is obvious that the result of tolerance is more than 0.1 and VIF less than 10, which indicates that the multicollinearity assumption was not violated.

Table 5.4
Collinearity Statistics

Observed variable	Tolerance	VIF
Innovative	0.555	1.801
Product Competitive	0.570	1.754
Aggressive	0.436	2.295
First-mover	0.683	1.464
System capabilities	0.733	1.363
Coordination capabilities	0.666	1.502
Socialisation capabilities	0.748	1.336
Experimentation	0.554	1.805
Acquisition	0.560	1.787

5.2 MEASUREMENT MODEL

The measurement model is comprised of the observed variables (indicators) and the underlying latent variables (constructs) that the indicators are presumed to measure. It is recommended that the measurement model be assessed independently prior to the structural model (Anderson & Gerbing, 1988). Procedures suggested by Garver and Mentzer (1999) involved independent assessment for unidimensionality of each latent variable to achieve an acceptable measurement model for each construct. This is followed by an assessment of the overall measurement model in the presence of other constructs. To assess unidimensionality, two criteria are observed, these being, the fit of the overall model and the fit of the components of the measurement model.

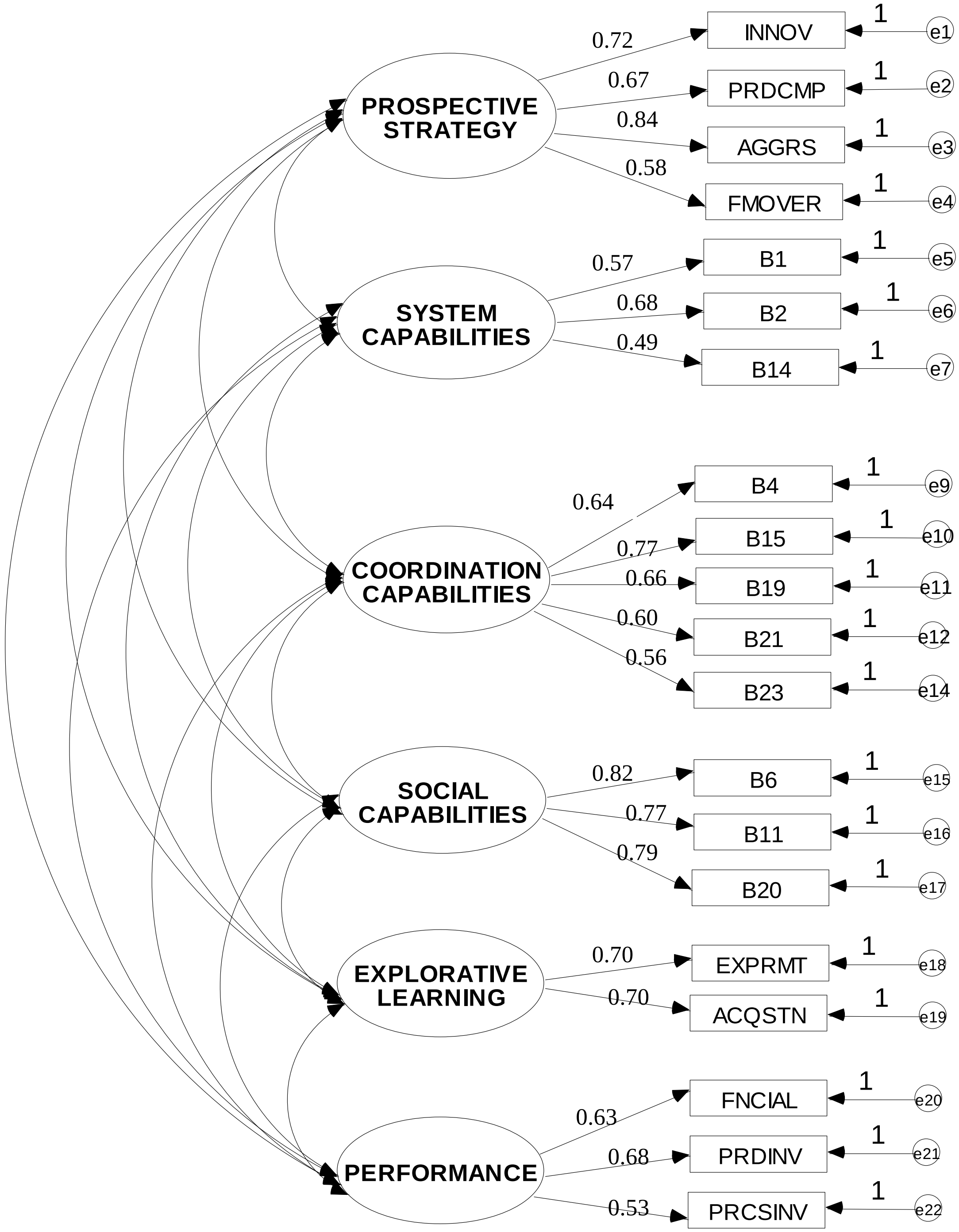


Figure 5.1
Measurement Model

Analysis of the measurement model was done by correlating all variables involved in the structural model. In Figure 5.1, every variable is assumed to be correlated with each other. The result of goodness of fit indices indicate a well-fitting model with $\chi^2 = 235.932$, df = 155, $p<0.05$; GFI = 0.900; TLI = 0.923; CFI = 0.937; and RMSEA = 0.050. From the inspection of the standardised regression weight, it is found that all items were significantly loaded into their intended factor with standard loadings ranging from 0.488 to 0.837. Further examination of modification indices (highest 8.673) and standardised residuals (highest 2.228) indicated that there was no cross-loading or misspecification in the model (Joreskog & Sorbom, 1988, recommended values not more than $\pm$ 2.58). Based on the result, there was no empirical or theoretical justification to modify or re-specify any of the existing relationships in the hypothesised model.

5.2.1 Discriminant Validity

The criteria in respect of unidimensionality were met when the standardised regression weight indicated that all items were significantly loaded into their intended factor with standardised loadings ranging from 0.49 to 0.84, and the fit indices indicating a well-fitting model in the measurement model (refer to Figure 5.1). However, as mentioned in the previous chapter, the model must not only fulfill the requirement of unidimensionality, but also meet the criteria of distinctiveness as measured by discriminant validity.

In this study, discriminant validity was measured by comparing the unconstrained model (that allows the correlations between constructs to be free) with the constrained model in which correlation of the two constructs was set to one (Anderson & Gerbing, 1988; Bagozzi & Philips, 1982). A Chi-square differences test was performed on the nested models to verify that the Chi-square for the unconstrained model was lower than for the constrained model (Anderson & Gerbing, 1988). The result as shown in Table 5.5 indicates significant Chi-square difference, where the critical value ($\Delta\chi^2 > 3.84$ for d.f =1) is exceeded in all cases, thereby providing evidence of discriminant validity. Therefore, it is sufficient to conclude that the model has met the criteria of distinctiveness and this confirmed the adequacy of the measurement model for subsequent testing in the structural form.

Table 5.5
CFA Comparison of the Measurement Models

Model	χ^2	df	GFI	TLI	CFI	RMSEA
6-Factor Model	235.932	155	0.900	0.923	0.937	0.050
4-Factor Model	450.847	164	0.804	0.743	0.778	0.092
3-Factor Model	506.556	167	0.787	0.702	0.738	0.099
2-Factor Model	560.112	169	0.772	0.660	0.698	0.106
1-Factor Model	720.505	170	0.692	0.525	0.575	0.125

Note: In the 6-factor model, all constructs are treated as four independent factors. In the 4-factor model, all combinative capabilities variables were loaded into one factor. In the 3-factor model, combinative capabilities and explorative learning items were loaded into one factor. In the 2-factor model, combinative capabilities, explorative learning and performance were loaded into one factor. Finally in the 1-factor model, all items were loaded into a single factor.

5.2.2 Convergent Validity

Convergent validity was measured based on the value of factor loadings of all observed variables (Anderson & Gerbing, 1988). As presented in Table 5.6, all factor loadings were statistically significant within the range of 0.488 to 0.837.

Table 5.6
Testing for Convergent Validity: Magnitude, Direction and Statistical Significance of the Estimated Parameters between Latent Variables and their Indicators

Factors/Items	Std. loading	Std. error	C.R	P
Innovative ← Prospector strategic orientation	0.717	0.090	10.336	***
Product competitiveness ← Prospector strategic orientation	0.673	0.120	8.734	***
Aggressive ← Prospector strategic orientation	0.837	0.104	10.336	***
First-Mover ← Prospector strategic orientation	0.582	0.124	7.604	***
B1 ← System Capabilities	0.568	0.285	4.857	***
B2 ← System Capabilities	0.676	0.176	5.607	***
B14 ← System Capabilities	0.488	0.149	4.857	***
B4 ← Coordination Capabilities	0.645	0.156	7.047	***
B15 ← Coordination Capabilities	0.770	0.135	8.406	***
B19 ← Coordination Capabilities	0.661	0.133	7.616	***
B21 ← Coordination Capabilities	0.598	0.129	7.047	***
B23 ← Coordination Capabilities	0.560	0.144	6.676	***
B6 ← Socialisation Capabilities	0.824	0.104	11.192	***
B11 ← Socialisation Capabilities	0.771	0.092	10.951	***
B20 ← Socialisation Capabilities	0.794	0.077	11.192	***
Experimentation ← Explorative Learning	0.697	0.100	8.891	***
Information Acquisition ← Explorative Learning	0.697	0.126	8.891	***
Financial ← Performance	0.630	0.235	5.392	***
Product Innovation ← Performance	0.681	0.161	5.953	***
Process Innovation ← Performance	0.530	0.147	5.392	***

In addition to convergent validity, construct validity was examined by measuring average variance extracted (AVE) and composite reliability which must exceed the recommended value of 0.70 and 0.50 (Bagozzi & Yi, 1988). As illustrated in Table 5.7, the average variance extracted (AVE) results ranged between 0.658 and 0.881 which exceeded the 0.50 recommended threshold, indicating that variance due to measurement error was smaller than variance captured by the construct. These results provide an indication of acceptable validity of the constructs. In other words, the indicators used in this study sufficiently represented the construct they were intended to qualify (Hair et al., 1998). The results of composite reliability provided further evidence that the measures used were internally consistent and exhibit satisfactory reliabilities.

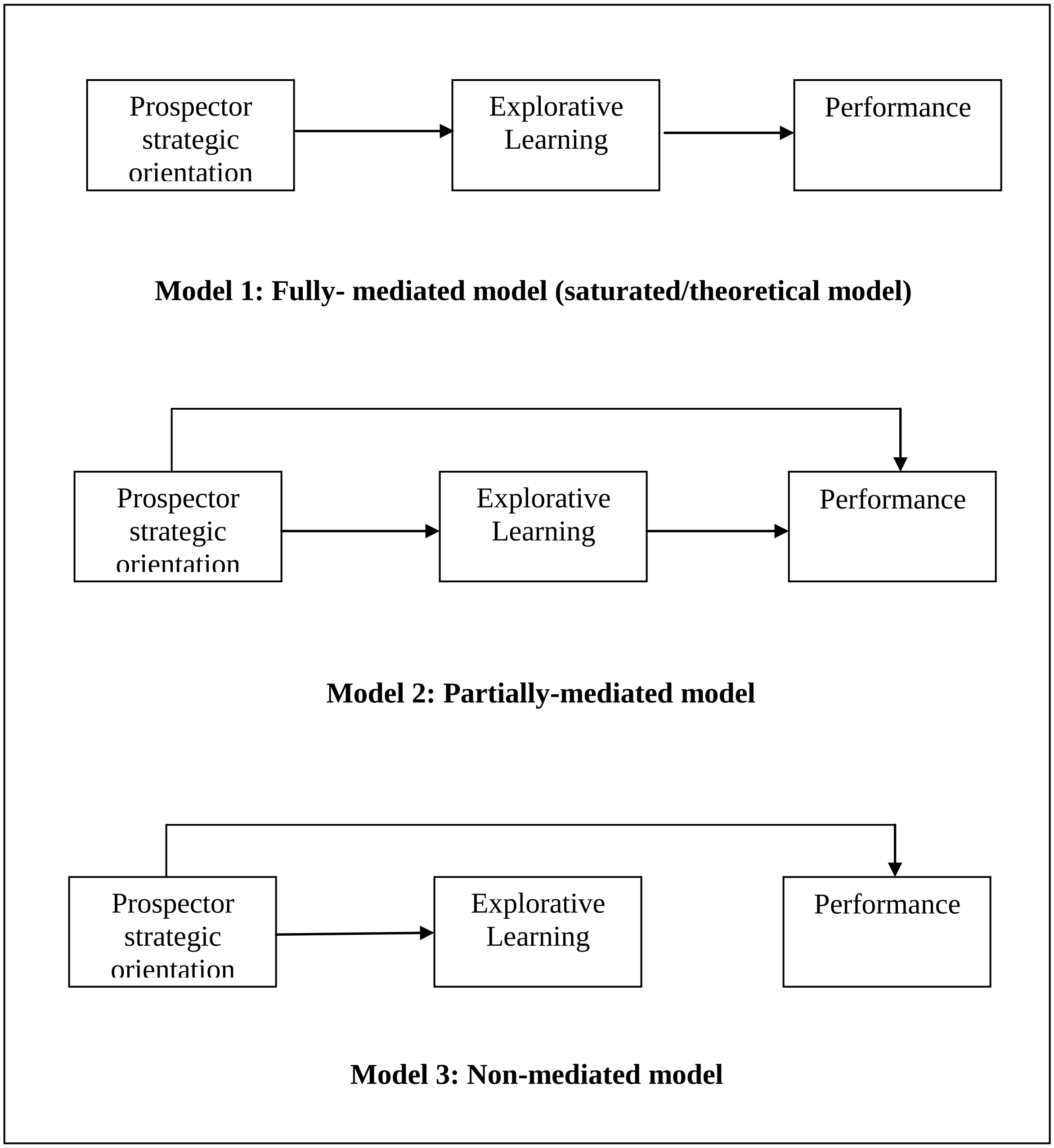
Table 5.7
Construct Reliability and Variance Extracted of Indicators

Constructs	Composite Reliability	Variance Extracted
Innovative	0.927	0.763
Product competitiveness	0.928	0.765
Aggressive	0.886	0.663
First-mover	0.769	0.658
System capabilities	0.867	0.687
Coordination capabilities	0.940	0.760
Socialisation capabilities	0.957	0.881
Experimentation	0.958	0.797
Information Acquisition	0.914	0.734
Financial	0.943	0.807
Product Innovation	0.929	0.814
Process Innovation	0.856	0.756

5.3 MEDIATION ANALYSIS

Prior analyses have confirmed that assumptions of SEM have not been violated and, therefore, the structural model can be developed and analysed. However, before the analysis can progress to the structural model, it is necessary to perform a mediation test to confirm the significant paths between variables that will best explain the whole model. For the purpose of mediation analysis, the procedure suggested by Baron and Kenny (1986) and Kelloway (1995) was adopted. Since the fully-mediated model and non-mediated model could not be directly compared because they were not nested models, both models were compared to partially-mediated models, since Kelloway (1995) suggested this as a remedy in such a case. The result of fit statistics and indices are then used to compare differences in goodness of fit measures and Chi-square statistics to determine the significance of paths in the model fit.

The analysis started with explorative learning as a mediator between prospector strategic orientation and performance. The full mediation model (with a direct path from prospector strategic orientation to performance was set to zero) was compared to the partially-mediated model. Then, the non-mediated model (with a path from explorative learning to performance was set to zero) was compared to the partially-mediated model (refer to the graphical presentation in Figure 5.2 that follows). The same procedure was repeated for other variables.



Model 1: Fully- mediated model (saturated/theoretical model)

Model 2: Partially-mediated model

Model 3: Non-mediated model

Figure 5.2
Graphical Representation of Mediation Analysis Procedure

5.3.1 Explorative Learning as Mediator

For the first mediation test, explorative learning was treated as the mediator in the relationship between prospector strategic orientation and performance. The result as shown in Table 5.8, indicated a non-significant improvement in the full mediation model (FM) ($\Delta\chi^2$ = 0.095**)** and non-mediation model (NM) ($\Delta\chi^2$ = 3.385**)** when compared to the partially-mediated model (PM). Due to the absence of significant improvement in both models, the significance of individual relationships in both models was examined. It was found that the direct relationship between prospector strategic orientation and performance was not significant (standardised loading = 0.089). Therefore, the full mediation model best explained the mediation effect of explorative learning in this relationship.

Table 5.8
Mediation Analysis 1: Comparison of Alternative Models

Mediation 1 : Prospector Strategic Orientation – Explorative Learning - Performance							
Model	χ^2	**df**	$\Delta\chi^2$	**GFI**	**TLI**	**CFI**	**RMSEA**
Model 1 (FM)	48.187	25	0.095*	0.949	0.938	0.957	0.067
Model 2 (PM)	48.092	24		0.949	0.933	0.955	0.070
Model 3 (NM)	51.475	25	3.383	0.945	0.929	0.951	0.072

*Significant at p<0.01. For 1 degree of freedom, the significant level of chi square differences test is set at 6.63 to guarantee that any modification of the hypothesised model is less likely to be an artefact of the sample used in this study.

For the second group of mediation tests, explorative learning was treated as the mediator in the relationship between combinative capabilities and performance. The mediation result summarised in Table 5.9 showed a non-significant change in Chi square between the full mediation model and the partial-mediation model, but a significant difference between the non-mediated model and the partially-mediated model in all types of combinative capabilities. For example, the mediating effect of explorative learning in system capabilities-performance relationship, there was a non-significant change in Chi square between the full mediation model and the partial-mediation model ($\Delta\chi^2$ = 1.939), but a significant difference between the non-mediated model and the partially-mediated model ($\Delta\chi^2$ = 11.893). Based on these results, it can be concluded that the full mediation model best explained the mediating effect of explorative learning in these relationships. To confirm this conclusion, direct relationships between variables were evaluated. It was found that the direct relationships between combinative capabilities and performance were not significant. Therefore, it was justified to accept that explorative learning fully mediated the relationship between system, coordination and socialisation capabilities, and performance.

Table 5.9
Mediation Analysis 2: Comparison of Alternative Models

Mediation 2a: System Capabilities – Explorative Learning - Performance							
Model	**χ^2**	**df**	**$\Delta\chi^2$**	**GFI**	**TLI**	**CFI**	**RMSEA**
Model 1 (FM)	28.992	18	1.939	0.966	0.940	0.962	0.054
Model 2 (PM)	27.053	17		0.968	0.942	0.965	0.053
Model 3 (NM)	38.946	18	11.893*	0.954	0.886	0.927	0.075
Mediation 2b : Coordination Capabilities – Explorative Learning - Performance							
Model	**χ^2**	**df**	**$\Delta\chi^2$**	**GFI**	**TLI**	**CFI**	**RMSEA**
Model 1 (FM)	46.721	33	0.382	0.956	0.962	0.972	0.045
Model 2 (PM)	46.329	32		0.957	0.959	0.971	0.047
Model 3 (NM)	59.168	33	12.839*	0.946	0.928	0.947	0.062

Table 5.9, continued

Mediation 2c: Socialisation Capabilities – Explorative Learning - Performance							
Model	**χ^2**	**df**	**$\Delta\chi^2$**	**GFI**	**TLI**	**CFI**	**RMSEA**
Model 1 (FM)	27.513	18	0.114	0.969	0.968	0.979	0.051
Model 2 (PM)	27.399	17		0.969	0.963	0.977	0.054
Model 3 (NM)	50.359	18	22.960*	0.945	0.890	0.929	0.093

*Significant at p<0.01. For 1 degree of freedom, the significant level of chi square differences test is set at 6.63 to guarantee that any modification of the hypothesised model is less likely to be an artefact of the sample used in this study.

5.3.2 Combinative Capabilities as Mediator

For the third group of mediation tests, combinative capabilities were treated as the mediator in the relationship between prospector strategic orientation and explorative learning (Mediation 3). The result, as shown in Table 5.10, indicated a significant improvement of fit from the partially-mediated model to the full-mediation model, and also significant improvement between the partially-mediated model and the non-mediated model in all relationships. For example, the mediating effect of system capabilities in prospector strategic orientation-explorative learning relationship, there was a significant change in Chi square between the full mediation model and the partial-mediation model ($\Delta\chi^2$ = 21.785), and a significant difference between the non-mediated model and the partially-mediated model ($\Delta\chi^2$ = 16.456). Since both comparisons showed significant improvement, an examination of goodness of fit of the nested model was required to ascertain the best model. Based on the result of goodness of fit, partial mediation best explained the mediation effect of system, coordination and socialisation capabilities in prospector strategic orientation – explorative learning relationship.

Table 5.10
Mediation Analysis 3: Comparison of Alternative Models

Mediation 3a: Prospector Strategic Orientation – System Capabilities - Explorative Learning							
Model	χ^2	**df**	$\Delta\chi^2$	**GFI**	**TLI**	**CFI**	**RMSEA**
Model 1 (FM)	62.862	25	21.785*	0.934	0.897	0.928	0.086
Model 2 (PM)	41.077	24		0.958	0.952	0.968	0.059
Model 3 (NM)	57.533	25	16.456*	0.941	0.912	0.939	0.079
Mediation 3b: Prospector Strategic Orientation – Coordination Capabilities - Explorative Learning							
Model	χ^2	**df**	$\Delta\chi^2$	**GFI**	**TLI**	**CFI**	**RMSEA**
Model 1 (FM)	133.945	42	57.526*	0.901	0.835	0.874	0.103
Model 2 (PM)	76.419	41		0.938	0.935	0.951	0.065
Model 3 (NM)	97.694	42	21.275*	0.922	0.900	0.924	0.080
Mediation 3c: Prospector Strategic Orientation – Socialisation Capabilities - Explorative Learning							
Model	χ^2	**df**	$\Delta\chi^2$	**GFI**	**TLI**	**CFI**	**RMSEA**
Model 1 (FM)	122.946	25	72.498*	0.896	0.796	0.858	0.138
Model 2 (PM)	50.448	24		0.950	0.943	0.962	0.073
Model 3 (NM)	59.029	25	8.581*	0.941	0.929	0.951	0.081

*Significant at p<0.01. For 1 degree of freedom, the significant level of chi square differences test is set at 6.63 to guarantee that any modification of the hypothesised model is less likely to be an artefact of the sample used in this study.

5.4 STRUCTURAL MODEL

Firstly, a structural model based on the hypothesised relationship was tested according to the goodness of fit indices. The result suggested that the hypothesised model demonstrated an acceptable fitting to the sample data of $\chi^2 = 271.065$, df = 162, $p<0.05$; GFI = 0.893; TLI = 0.908; CFI = 0.916; and RMSEA = 0.057. A further check on the standardised residuals showed values below 2.58 (highest 2.455), indicating that there was no cross-loading or misspecification among the variables in the hypothesised model (Byrne, 2001). The values of MI for the structural paths posed nothing of concern.

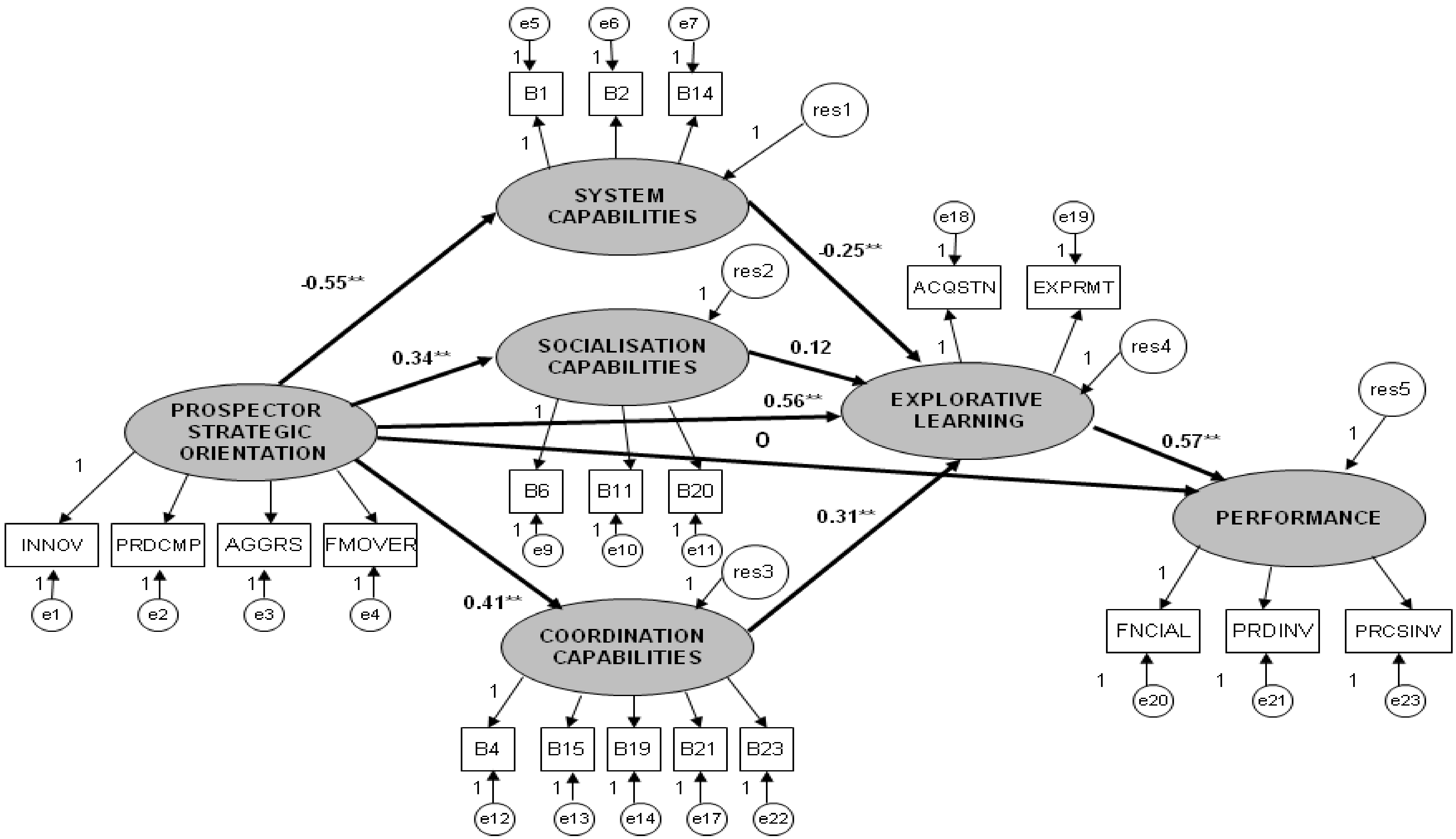


Figure 5.3
Hypothesised Full Information Structural Model

An examination of the structural model in figure 5.3 indicates significant paths between prospector strategic orientation and explorative learning (standardised coefficient = 0.56), system capabilities (standardised coefficient = -0.55) and coordination capabilities (standardised coefficient = 0.41). Significant paths are also observed between explorative learning and performance (standardised coefficient = 0.57), system capabilities (standardised coefficient = -0.25) and coordination capabilities (standardised coefficient = 0.31). These findings are summarised in table 5.11.

Table 5.11
Hypothesis Testing Results from Structural Model:
Direct, Indirect and Total Effect

Hypothesised Relationships	Direct effect	Indirect effect	Total effect
Prospector strategic orientation → Performance		0.492**	0.492**
Explorative Learning → Performance	0.57**	-	0.571**
Prospector strategic orientation → Explorative Learning	0.556**	0.305**	0.861**
Prospector strategic orientation → System Capabilities	-0.545**	-	-
Prospector strategic orientation → Coordination Capabilities	0. 411**	-	-
Prospector strategic orientation → Socialisation Capabilities	0. 339	-	-
System Capabilities → Explorative Learning	-0.253**	-	-
Coordination Capabilities → Explorative Learning	0.313**	-	-
Socialisation Capabilities → Explorative Learning	0.12	-	-
System Capabilities → Performance	-	-0.145**	-
Coordination Capabilities → Performance	-	0.179**	-
Socialisation Capabilities → Performance	-	0.066	-

** indicates the result is significant and supports the hypothesised relationship

5.5 DIRECT EFFECT, INDIRECT EFFECT AND TOTAL EFFECT

Total causal effect between variables can be decomposed into a direct and an indirect effect. Direct effect represents the direct effect of one variable on another variable, while indirect effect involves causal effect of one or more intervening variables between prior variables and subsequent variables (Kline, 1998). To measure direct effect, the partial coefficient between two variables was measured by controlling all prior variables and intervening variables in the model. On the other hand, indirect effect was measured by the product of standardised coefficients of the paths linking the two variables (Bentler, 1995). The results of direct, indirect and total effect are summarised in Table 5.11.

5.5.1 Direct Effect

From the hypothesised structural model, prospector strategic orientation has a significant positive effect (standardised coefficient = 0.556) on explorative learning. This indicated that firms with greater prospector orientation engaged more in explorative learning. Prospector strategic orientation was positively related to coordination capabilities (standardised coefficient = 0.411) and socialisation capabilities (standardised coefficient = 0.339), but negatively related to system capabilities (standardised coefficient = -0.545). In other words, firms with prospector strategic orientation will put in place greater organisational mechanisms to encourage coordination and socialisation capabilities but less for system capabilities. In terms of the variance explained, prospector strategic orientation explained 52% of the total variance in combinative capabilities.

As for the direct effects of combinative capabilities on explorative learning, coordination capabilities has a significant positive direct effect on explorative learning (standardised coefficient = 0.313). On the other hand, system capabilities has a significant negative direct effect on explorative learning (standardised coefficient = -0.253). This implies that explorative learning will be enhanced by greater coordination capabilities with lower system capabilities. Prospector strategic orientation and combinative capabilities explained 86% of the total variance in explorative learning. Finally, all the variables involved explained 49% of total variance in performance.

5.5.2 Indirect Effect

Prospector strategic orientation has a significant positive indirect effect on explorative learning (standardised coefficient = 0.305) and performance (standardised coefficient = 0.492). As for combinative capabilities, coordination capabilities has a significant positive indirect effect on performance (standardised coefficient = 0.179) and system capabilities has a significant negative indirect effect on performance (standardised coefficient = -0.145).

The result implies that prospector strategic orientation has a significant indirect effect on explorative learning through combinative capabilities. In addition, combinative capabilities have a significant indirect effect on performance through explorative learning.

5.5.3 Total Effect

Finally, total effects are the sum of all direct effects and indirect effects of one variable on another variable. The total effect of prospector strategic orientation on explorative learning was 0.861, prospector strategic orientation and performance was 0.492 and explorative learning and performance was 0.571.

5.6 SUMMARY OF FINDINGS ON HYPOTHESISED RELATIONSHIPS

The analysis of the hypotheses can be divided into five clusters based on the research questions:

i. direct hypotheses that relate prospector strategic orientation and explorative learning to performance;
ii. direct hypotheses that relate prospector strategic orientation to explorative learning and combinative capabilities;
iii. direct hypotheses that relate combinative capabilities and explorative learning;
iv. hypotheses that explain mediated relationships between variables;
v. hypothesis that explain the mediating role of both combinative capabilities and explorative learning in the relationship between prospector strategic orientation and performance.

5.6.1 Hypothesis 1: Hypotheses related to Performance

Table 5.12
Hypotheses related to performance

Hypotheses	Findings
1a. Prospector strategic orientation is positively related to performance.	Not supported
1b. Explorative learning is positively related to performance	Supported

As summarised in Table 5.12, the main hypotheses concerning prospector strategic orientation and explorative learning and performance, provided mixed results. The proposition of a positive relationship between prospector strategic orientation and performance was not supported. In other words, the notion that strategy will determine performance was rejected in this study. On the other hand, explorative learning was found to be significantly positively related to performance.

5.6.2 Hypothesis 2: Hypotheses related to Prospector Strategic Orientation

Table 5.13
Hypotheses related to Prospector Strategic Orientation

Hypotheses	Findings
2a. Prospector strategic orientation is positively related to explorative learning.	Supported
2b. Prospector strategic orientation is negatively related to system capabilities	Supported
2c. Prospector strategic orientation is positively related to coordination capabilities.	Supported
2d. Prospector strategic orientation is negatively related to socialisation capabilities	Not supported

Prospector strategic orientation was found to be significantly positively related to explorative learning and this was well supported by past findings (Auh and Menguc, 2005). Prospector strategic orientation was found to be significant negatively related to system capabilities and positively related to coordination capabilities. Both results indicated support for the proposed hypotheses. However, the relationship between prospector strategic orientation and socialisation capabilities was positively significant which contradicted the proposed hypothesis of a negative relationship. In other words, hypothesis 2d was not supported.

5.6.3 Hypothesis 3: Hypotheses related to Combinative Capabilities and Explorative Learning

Table 5.14
Hypotheses related to Combinative Capabilities and Explorative Learning

Hypotheses	Findings
3a. System capabilities are negatively related to explorative learning	Supported
3b. Coordination capabilities are positively related to explorative learning	Supported
3c. Socialisation capabilities are negatively related to explorative learning	Not supported

Table 5.14 explains the result for the hypotheses that related combinative capabilities and explorative learning. System capabilities were found to be negatively related to explorative learning and coordination capabilities were found to be positively related. Both hypotheses were supported by the findings. However, the relationship between socialisation capabilities and explorative learning was found to be insignificant and in the opposite direction.

5.6.4 Hypothesis 4: Hypotheses related to Mediated Relationships

Table 5.15
Hypotheses related to Mediated Relationships

Hypotheses	Findings
4a. Explorative learning partially mediates the relationship between prospector strategic orientation and performance.	Not supported
4b. System capabilities partially mediate the relationship between prospector strategic orientation and explorative learning.	Supported
4c. Coordination capabilities partially mediate the relationship between prospector strategic orientation and explorative learning.	Supported
4d. Socialisation capabilities partially mediate the relationship between prospector strategic orientation and explorative learning.	Supported
4e. Explorative learning fully mediates the relationship between system capabilities and performance.	Supported
4f. Explorative learning fully mediates the relationship between coordination capabilities and performance.	Supported
4g. Explorative learning fully mediates the relationship between socialisation capabilities and performance.	Supported

Table 5.15 illustrates the results of hypotheses-testing for the mediated relationships as postulated in this study. The study proposed that explorative learning partially mediates the relationship between prospector strategic orientation and performance; however the findings indicated that there was no direct relationship between prospector strategic orientation and performance. In other words, the relationship between prospector strategic orientation and performance was fully mediated by explorative learning and, therefore, the proposed hypothesis of partial mediation was not supported.

However, the proposal of partial mediation of combinative capabilities in a prospector strategic orientation-explorative learning relationship was well supported. The findings also indicated that explorative learning fully mediated the relationship between system, coordination, and socialisation capabilities and performance. In other words, all three proposed hypotheses of the mediation effect of combinative capabilities in the explorative learning-performance relationship were supported. In terms of the mediation effect of explorative learning between combinative capabilities and performance, the study proposed full mediation. In other words, combinative capabilities have no direct effect on performance but are being fully mediated by explorative learning. The findings revealed that full mediation of explorative learning in this relationship was well supported.

5.6.5 Hypothesis 5: Hypothesis related to Mediation of Combinative Capabilities and Explorative Learning in Prospector Strategic Orientation and Performance Relationship

Table 5.16
Hypothesis related to Mediation of Combinative Capabilities and Explorative Learning in Prospector Strategic Orientation and Performance Relationship

Hypotheses	Findings
5a. Both combinative capabilities and explorative learning mediate the relationship between prospector strategic orientation and firm performance	Supported

Based on the result of SEM, an acceptable structural model was achieved that justifies the conclusion that both combinative capabilities and explorative learning mediate the relationship between prospector strategic orientation and performance, and this will sufficiently explain variation in performance. The goodness of fit indices suggested that the hypothesised model demonstrated an acceptable fitting to the sample data. This supports the alignment proposition of internal factors in strategy-performance relationship that was proposed in the strategic management literature based on contingency perspective.

5.7 CONCLUSION

This chapter presented the result of SEM analysis by firstly determining the adequacy of the data in meeting the SEM requirements. After confirming the assumptions, the analysis moved to the next level by developing the structural model and based on the statistical results, hypothesis-testing was performed. The findings showed that prospector strategic orientation was negatively related to system capabilities and positively related to coordination and socialisation capabilities. It was also found that prospector strategic orientation was significantly related to explorative learning and the relationship was partially mediated by combinative capabilities. However, the direct positive relationship between prospector strategic orientation and performance was not supported, but the findings indicated that the relationship was being fully mediated by explorative learning. Based on mediation analysis, the relationship between combinative capabilities and performance was being fully mediated by explorative learning. Finally, the findings also support the contention of alignment of internal constructs in strategy-performance relationship as argued in the literature. Detailed discussion of the results of hypothesis-testing will be presented in the subsequent chapter.