CHAPTER 5

COMPETITIVE ADVANTAGES OF CEP SERVICE PROVIDERS IN TIMES OF DISRUPTIONS

5.1 Introduction

This chapter is about identifying the various factors that give an edge over other CEP service providers in a disruptive environment. Statistical tool, such as factor analysis, is used to group the variables and determine the competitive advantages of CEPs.

5.2 Identification of competitive advantages parameters

5.2.1 Descriptive statistics of factors:

The descriptive statistics give a more detailed picture of the data by pointing out important information about how the factors were distributed and what their main trends were. It can be seen from the relatively low standard errors of the mean, the mean scores, which are mostly between 4.7 and 5.0, show that respondents have a generally positive view of all aspects. The standard deviations, which are about 1.0 to 1.7, show that responses were moderately different. Some questions, like those under *synergistic adaptation* and *disruption preparedness*, had higher dispersion, which means that respondents had a wider range of opinions. Most of the items have a small negative skew ranging from -0.317 to 0.545, which means that most of them got higher ratings. However, some items in the *disruption preparedness* category have a positive skew, which means that people tend to give these areas lower ratings. The kurtosis values show more about the distribution. Most of the items have negative kurtosis, ranging from -0.868 to 0.082, which means that the distribution is flatter and there are fewer extreme values. However, some items, like disruption preparedness 2, have positive kurtosis, which means that there are heavier tails, which could mean that these responses are outliers. These differences between the data points show that they are not perfectly normal, but they are not too big or too small. Small to moderate deviation from normality is not a problem if the sample is large enough (Spencer et al., 2017). These deviations usually don't cause big problems, especially when strong statistical methods are used that don't assume strict normality (for example, PLS-SEM) (Hair et al., 2012).

Table 5.1 Descriptive statistics of competitive preparedness indicators

Parameters	*Mean*	*Std. Error of Mean*	*Std. Deviation*	*Skewness*	*Kurtosis*
Logistics Excellence 1	4.98	.189	1.313	-.490	-.330
Logistics Excellence 2	4.73	.210	1.455	-.629	.492
Logistics Excellence 3	4.73	.218	1.512	-.133	-.904
Logistics Excellence 4	4.92	.199	1.381	-.350	-.011
Logistics Excellence 5	4.60	.204	1.410	-.340	-.391
Operating efficiency 1	4.69	.158	1.095	-.250	.388
Operating efficiency 2	4.98	.162	1.120	-.147	-.099
Operating efficiency 3	4.98	.172	1.194	-.428	-.153
Operating efficiency 4	4.77	.158	1.096	-.027	.073
Operating efficiency 5	4.98	.180	1.246	-.235	-.563
Operating efficiency 6	5.02	.150	1.041	-.279	-.652
Innovation 1	5.00	.179	1.238	-.492	.136
Innovation 2	4.67	.144	.996	-.753	.613
Innovation 3	4.77	.166	1.153	-.050	-.329
Innovation 4	4.69	.189	1.307	-.042	-.650
Synergistic Adaptation 1	4.88	.228	1.579	-.529	-.451
Synergistic Adaptation 2	4.79	.244	1.688	-.710	.077
Synergistic Adaptation 3	4.83	.231	1.602	-.494	-.323
Disruption preparedness 1	4.58	.190	1.318	-.392	.226
Disruption preparedness 2	4.54	.191	1.320	-.297	.923
Disruption preparedness 3	4.33	.207	1.434	.147	-.739
Disruption preparedness 4	4.29	.193	1.336	-.397	-.391
Disruption preparedness 5	4.35	.180	1.246	.245	-.142
Disruption preparedness 6	4.33	.191	1.326	-.137	.484
Performance 1	4.94	.203	1.405	-.701	.276
Performance 2	4.73	.192	1.333	-.040	-.646
Performance 3	4.71	.213	1.473	-.178	-.797
Performance 4	4.79	.200	1.383	-.263	.011

5.2.2 Exploratory factor analysis

The study included five uncertainty preparedness components analyzed using principal component analysis with varimax rotation as the extraction method for factor analysis. Prior to analyzing the factors, it is essential to assess the data's applicability using the KMO, Bartlett test, and anti-image correlation matrix. The KMO value was above the recommended threshold of 0.7, indicating adequate sampling, while Bartlett's Test was significant ($p < 0.001$), suggesting that the correlation matrix was suitable for factor analysis. Both of these tests yielded substantial findings. Variables were included in factors based on their factor loadings over 0.5, and factors with eigenvalues above 1.0 were retained. The next phase involved evaluating the communality of each variable to determine which item loadings are significant for interpreting the factors. The communalities of all variables exceeded 0.50, confirming that the factors provided a satisfactory explanation of the variables. SPSS was utilized to extract the variables, leading to the discovery of five factors that together accounted for 83.65% of the overall variance. This finding emphasizes a clearly specified configuration of factors, successfully including the primary aspects of uncertainty preparedness in the dataset.

Table 5.2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		*.891*
Bartlett's Test of Sphericity	Approx. Chi-Square	1206.872
	df	276
	Sig.	.000

Table 5.3 Total Variance Explained

Component	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	14.093	58.723	58.723	14.093	58.723	58.723	4.814	20.057	20.057
2	2.168	9.034	67.757	2.168	9.034	67.757	4.703	19.596	39.653
3	1.550	6.457	74.214	1.550	6.457	74.214	4.243	17.681	57.334
4	1.219	5.078	79.292	1.219	5.078	79.292	3.330	13.873	71.207
5	1.046	4.358	83.650	1.046	4.358	83.650	2.986	12.443	83.650
6	.532	2.218	85.869						
7	.505	2.103	87.972						
8	.394	1.643	89.615						
9	.351	1.463	91.078						
10	.304	1.268	92.346						
11	.262	1.091	93.437						
12	.250	1.044	94.481						
13	.233	.972	95.453						
14	.201	.839	96.292						
15	.161	.671	96.963						
16	.147	.614	97.577						
17	.118	.493	98.071						
18	.104	.432	98.502						
19	.092	.385	98.887						
20	.082	.343	99.230						
21	.063	.264	99.494						
22	.052	.215	99.709						
23	.038	.156	99.865						
24	.032	.135	100.000						

Extraction Method: Principal Component Analysis.

Table 5.4 Rotated Component matrix

	Component				
	1	2	3	4	5
DSP6	.809				
DSP1	.785				
DSP2	.785				
DSP3	.748				
DSP5	.739				
DSP4	.729				
OE2		.816			
OE4		.745			
OE6		.744			
OE1		.742			
OE5		.710			
OE3		.661			
LE1			.801		
LE5			.794		
LE3			.762		
LE2			.755		
LE4			.737		
INV2				.850	
INV1				.769	
INV3				.753	
INV4				.694	
SA1					.832
SA3					.806
SA2					.782

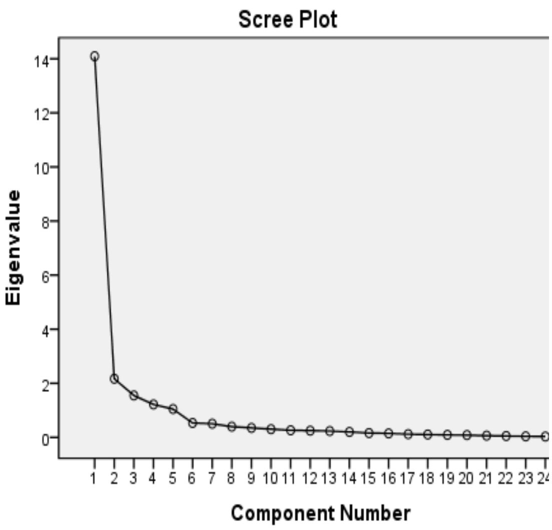
Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

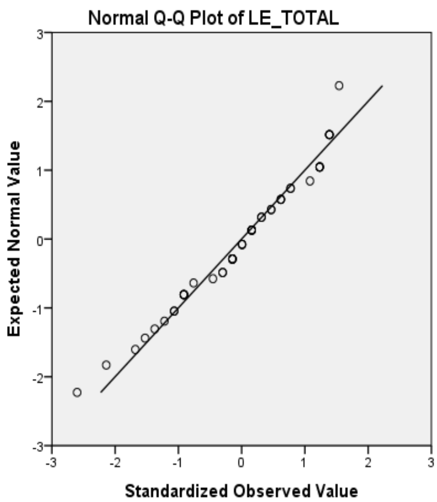
Factor analysis extracts the variables, leading to the discovery of five constructs grouped from 24 sub-indicators that together accounted for 83.65% of the overall variance. The factors identified were named as *logistics excellence, operating efficiency, innovation, synergistic adaptation, and disruption preparedness*. The factor loadings are all satisfactory and above 0.5, indicating a clearly specified configuration of factors, successfully including the primary aspects of uncertainty preparedness in the dataset.

Screen plot and Q-Q plot of the component analysis

A scree plot displays the eigenvalues obtained from a factor analysis, emphasizing the amount of variance accounted for by each component. A significant decrease in eigenvalues following the first component suggests that the initial components effectively explain much of the variability in the dataset. An important indicator for estimating the number of significant components is the elbow point, which is seen around the fifth component. After this point, the eigenvalues stabilize, indicating that subsequent components make only insignificant contributions to explaining the variance. Crucially, the initial five components display eigenvalues that exceed 1, indicating that they encompass the majority of the significant variation in the data. Therefore, our research will focus on these five components, as they are likely to reflect the fundamental underlying structure of the dataset. The decision is substantiated by factor analysis and the rotation of the component matrix, which guarantees a strong and reliable depiction of the inherent variability in the data.

The accompanying Q-Q figure provides a more comprehensive evaluation of the distribution of the components, indicating that the data strongly conforms to the anticipated normal distribution. Most data points were found in close proximity to the 45-degree reference line, suggesting an approximation normal distribution. Nevertheless, there are smaller variations at the extremes, indicating possible outliers or little skewness. Although not significant, these deviations should be considered in statistical models that rely on assumptions of normality. In general, the data is suitable for most studies that make the assumption of normalcy, with only minor modifications needed for more rigorous mathematical models.





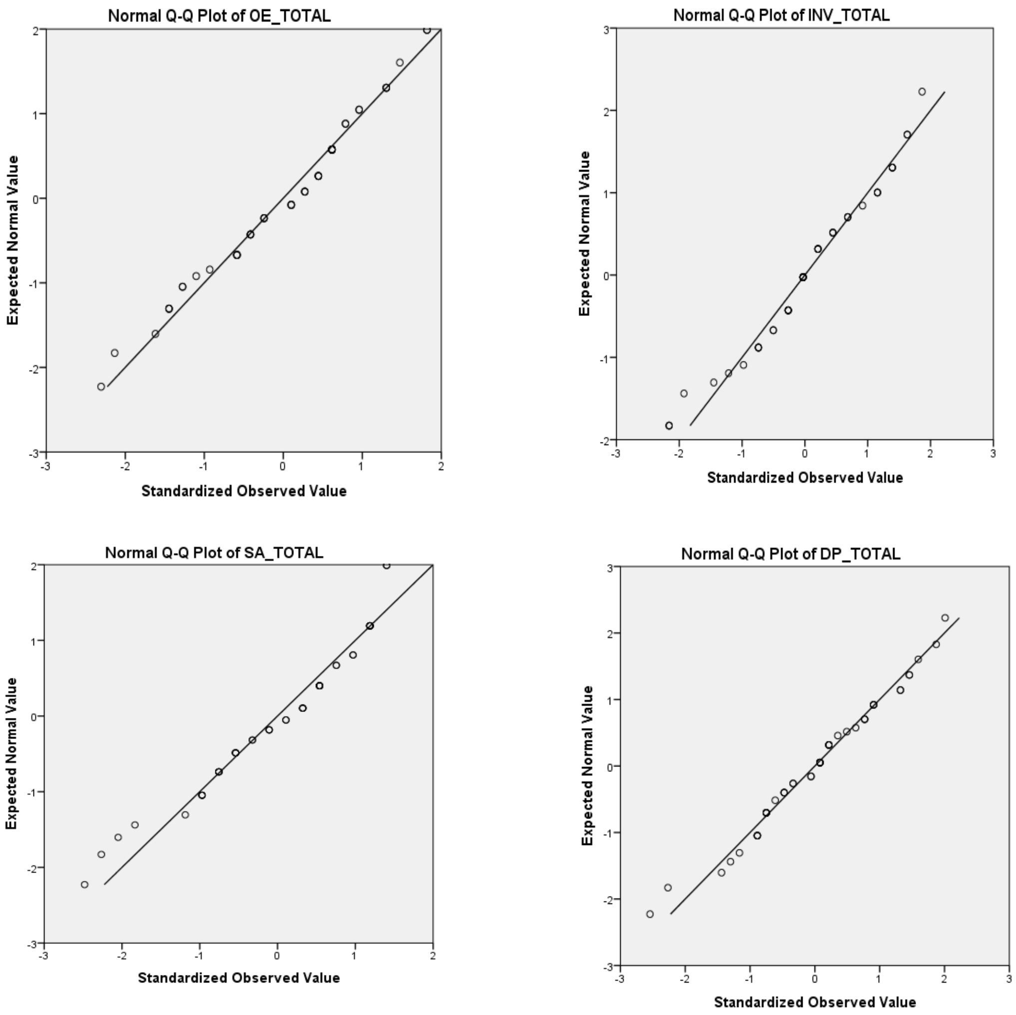


Figure 5.1 Screen plot of the eigenvalues and Q-Q plot of components

5.2.3 Sub-indicator coding and weights

Table 5.5 Sub-indicator coding and weights for competitive preparedness

Constructs	*Codes*	*Indicators*	*Indicator Weight*
Logistics Excellence	LE1	Accurate delivery	0.64
	LE2	Security during transit	0.57
	LE3	Less number of rejected/undelivered items	0.56
	LE4	Notification and alerts for accurate delivery status	0.54
	LE5	Timely and reliable pickup/delivery	0.63
Operating efficiency (OE)	OE1	Flexibility in operation	0.55
	OE2	Express or time-sensitive deliveries	0.66
	OE3	Short processing time and in transit time	0.43
	OE4	Cost-effective services	0.56
	OE5	Short response time for queries and conflicts	0.5
	OE6	Delivery agent's efficiency	0.55
Innovation	INV1	Technological advancement	0.59
	INV2	Novel delivery solutions or services	0.72
	INV3	Adapted the operational processes	0.57
	INV4	Advancement in organizational process	0.48

Constructs	Codes	Indicators	Indicator Weight
Synergistic Adaptation	SA1	Adaptability	0.69
	SA2	Alignment	0.61
	SA3	Agility	0.65
Disruption preparedness	DSP1	Geographical coverage	0.61
	DSP2	Distribution centers and modes of transportation	0.62
	DSP3	Resource utilization	0.56
	DSP4	Collaborations	0.53
	DSP5	Risk management	0.53
	DSP6	Efficient human resources	0.54
Performance	PERF1	Sales growth	
	PERF2	Market reach	
	PERF3	Profitability	
	PERF4	Customer satisfaction	

Table 5.5 displays the coding and sub-indicator weights for the constructs related to uncertainty preparedness that were identified in the study. There are five sub-indicators related to logistics excellence, six sub-indicators related to operating efficiency, four sub-indicators related to innovation, three sub-indicators related to synergistic adaptation, and six sub-indicators related to disruption preparedness. The indicators are denoted by different codes, each with weights that indicate their level of importance. The weights assigned to each item indicate the degree to which it contributes to its corresponding construct, therefore offering valuable insights into the fundamental aspects of uncertainty preparedness.

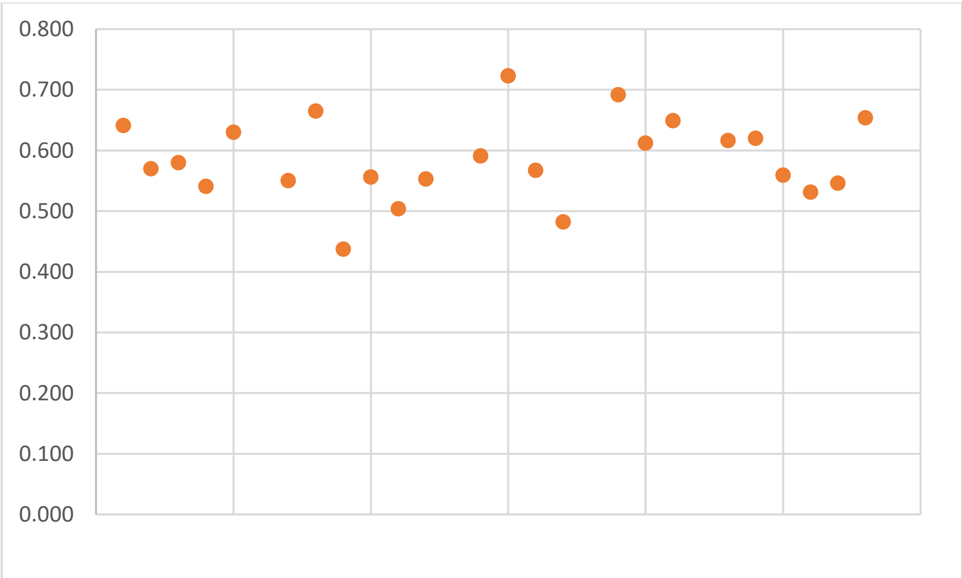


Figure 5.2 Scatter plot of sub-indicators weight

The scatter plot does not exhibit any extreme outliers that would markedly diverge from the overall cluster of dots. The majority of data points are concentrated between 0.5 and 0.7, signifying that most measures reside within a modest performance range. This aligns with the presented table, where many criteria, including *accurate delivery* (0.641) and *timely and reliable pickup/delivery* (0.630), exhibit comparable results. However, certain indicators fall below 0.5, perhaps indicating suboptimal performance, such as *short processing time and in transit time* (0.437). The plot indicates a consistent performance across attributes, with minimal extreme variations. This visual summary emphasizes both the important and less important areas in the examined preparedness measures. The scatter plot illustrates numerous notable points, indicating elevated values on the y-axis, denoting exceptional performance in particular criteria. The greater values, above 0.7, probably relate to qualities with notably high scores. The plot indicates that *novel delivery solutions or services* (0.723) and *adaptability* (0.692) demonstrate elevated values, signifying their enhanced performance relative to other criteria.

5.3 Relationship between competitive advantage factors and business performance

5.3.1 Correlation analysis

The correlation matrix in Table 5.7 illustrates the correlations among the five components of uncertainty preparedness and their overall effect on business performance. All dimensions exhibit substantial positive relationships with one another, suggesting that advancements in one domain, such as logistics or innovation, are likely to boost performance and efficiency in other domains. Nonetheless, operating efficiency and disruption preparedness are particularly crucial components in achieving high levels of performance.

Table 5.6 Correlation matrix of competitive preparedness

	LE	*OE*	*INV*	*SA*	*DP*	*PERF*
LE	1					
OE	.668**	1				
INV	.691**	.578**	1			
SA	.555**	.703**	.484**	1		
DP	.711**	.654**	.667**	.637**	1	
PERF	.789**	.790**	.761**	.741**	.798**	1
*** P < 0.05*						

5.3.2 Assessment of measurement model:

This part of the study looks at the measurement model's properties in detail, using a number of tests to make sure the index score that was calculated is correct. As part of the evaluation, factor loadings, composite reliability, and both convergent and discriminant validity are looked at. These methods are very important for making sure that the study's constructs are correctly modeled and that the model properly shows how the variables are related to each other. The study also uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypotheses. This gives a strong structure for looking at the suggested connections and proving the theoretical model. The measurement model's reliability and accuracy are proven by this thorough evaluation, which sets a solid base for further data analysis and interpretation.

Table 5.7 Outer loadings, reliability and validity of constructs

Factors	*Outer Loadings*	*Cronbach's alpha*	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	*Average variance extracted (AVE)*	*VIF*
DP1	0.912	0.957	0.959	0.966	0.825	4.72
DP2	0.916					4.75
DP3	0.928					5.19
DP4	0.867					3.06
DP5	0.892					3.77
DP6	0.933					5.70
INV1	0.914	0.920	0.930	0.943	0.806	3.46
INV2	0.862					2.61
INV3	0.916					3.41
INV4	0.897					2.82
LE1	0.943	0.956	0.958	0.966	0.851	5.81
LE2	0.920					4.26
LE3	0.924					4.99
LE4	0.893					3.81
LE5	0.930					5.34
OE1	0.871	0.928	0.928	0.943	0.735	2.99
OE2	0.912					4.64
OE3	0.843					2.44
OE4	0.842					3.01
OE5	0.831					2.63
OE6	0.844					2.51
SA1	0.949	0.948	0.954	0.967	0.906	4.85
SA2	0.959					5.20
SA3	0.947					4.60
PERF1	0.923	0.933	0.935	0.952	0.832	3.94
PERF2	0.888					2.90
PERF3	0.927					3.90
PERF4	0.910					3.42

5.3.2.1 Reliability and validity:

Subsequently, a reflective measurement model evaluation was conducted to verify the reliability and validity of the measurement scales for twelve dimensions, which were established following an exploratory factor analysis (EFA).

- ***Composite Reliability (CR):*** Table 5.8 demonstrates that the composite reliability (CR) values of constructs were all over 0.7, with a range of 0.943 to 0.966, indicating high reliability. Cronbach's alpha value was also above 0.7. This discovery validated the notion that the measuring scales provide a sufficient level of internal consistency reliability for a new scale, as stated by Hair et al. (2019).
- ***Convergent validity:*** The average variance extracted (AVE) of all constructs was higher than 0.5, indicating that the measurement scales have adequate convergent validity.
- ***Discriminant Validity:*** The Fornell-Larcker criterion in Table 5.10 confirms the presence of discriminant validity, as all square roots of the average variance extracted (AVE) are greater than the corresponding correlations between the components. The cross-loading results, similar to the Fornell-Larker criterion, indicate that all the constructs demonstrated discriminant validity, as none of the cross-loading values were below 0.1 (Chin, 1998). Furthermore, all the indicators exhibit a significant degree of loading on the relevant constructions rather than other constructs. This observation suggests that each of the constructs inside the framework exhibits a high degree of distinctiveness from the others. The findings of cross-loading are presented in the Appendix. The HTMT values also suggest the validity with the values greater than 0.85. The findings of the HTMT are presented in Table 5.9. Consequently, it has been verified that all the constructs demonstrated satisfactory levels of discriminant validity.
- ***Construct validity:*** The convergent validity and discriminant validity establish construct validity of this study.

Table 5.8 Heterotrait-monotrait ratio (HTMT) - Matrix

	DP	*INV*	*LE*	*OE*	*PERF*	*SA*
DP						
INV	0.709					
LE	0.742	0.732				
OE	0.690	0.617	0.708			
PERF	0.845	0.814	0.833	0.847		
SA	0.668	0.507	0.581	0.750	0.786	

Table 5.9 Fornell-Larcker criterion

	DP	INV	LE	OE	PERF	SA
DP	0.908					
INV	0.669	0.898				
LE	0.710	0.691	0.922			
OE	0.652	0.578	0.666	0.858		
PERF	0.799	0.763	0.791	0.790	0.912	
SA	0.639	0.490	0.556	0.704	0.743	0.952

5.3.2.2 Common method variance (CVM)

The study used a rigorous way to reduce bias from self-reported data by applying a comprehensive technique specifically designed for this purpose. The measurement approach utilized collinearity statistics, focusing on evaluating the variance inflation factor (VIF) with a stringent threshold of VIF values equal to or below 5 (Hair et al., 2019). However, for four items, VIF<10 is considered a threshold (James et al., 2017). The study used Harman's (1967) single-factor test and conducted unrotated principal component factor analysis in SPSS. The research identified ten separate factors of service quality with eigenvalues of 1.00 or above, explaining a total of 83.65% of the variation, which contradicts the idea of a single underlying factor. The common approach variance was found to be less than 50%, with the first factor accounting for 20.057% of the variance, in line with Podsakoff et al.'s (2003) suggestions. The study also took into account the thresholds proposed by Afum et al. (2020) for reflective models, stating that a VIF value lower than 3.3 indicates the absence of common method bias. The study chose a conservative approach, in line with Kock's (2015) assertion that a VIF of 5 or less is required to tackle potential multicollinearity difficulties.

5.3.3 Structural Equation Model

5.3.3.1 Hypothesis testing

Table 5.10 Path coefficient of PLSSEM

Paths	Path coefficients	SE	Bias corrected at 95% confidence interval		T values	P values	Decision
			2.5%	**97.5%**			
DP -> PERF	0.199	0.091	0.043	0.423	2.185	0.029	Supported
INV -> PERF	0.252	0.114	0.022	0.460	2.215	0.027	Supported
LE -> PERF	0.203	0.088	0.025	0.372	2.298	0.022	Supported
OE -> PERF	0.221	0.108	-0.025	0.411	2.045	0.041	Supported
SA -> PERF	0.223	0.074	0.086	0.375	3.027	0.002	Supported

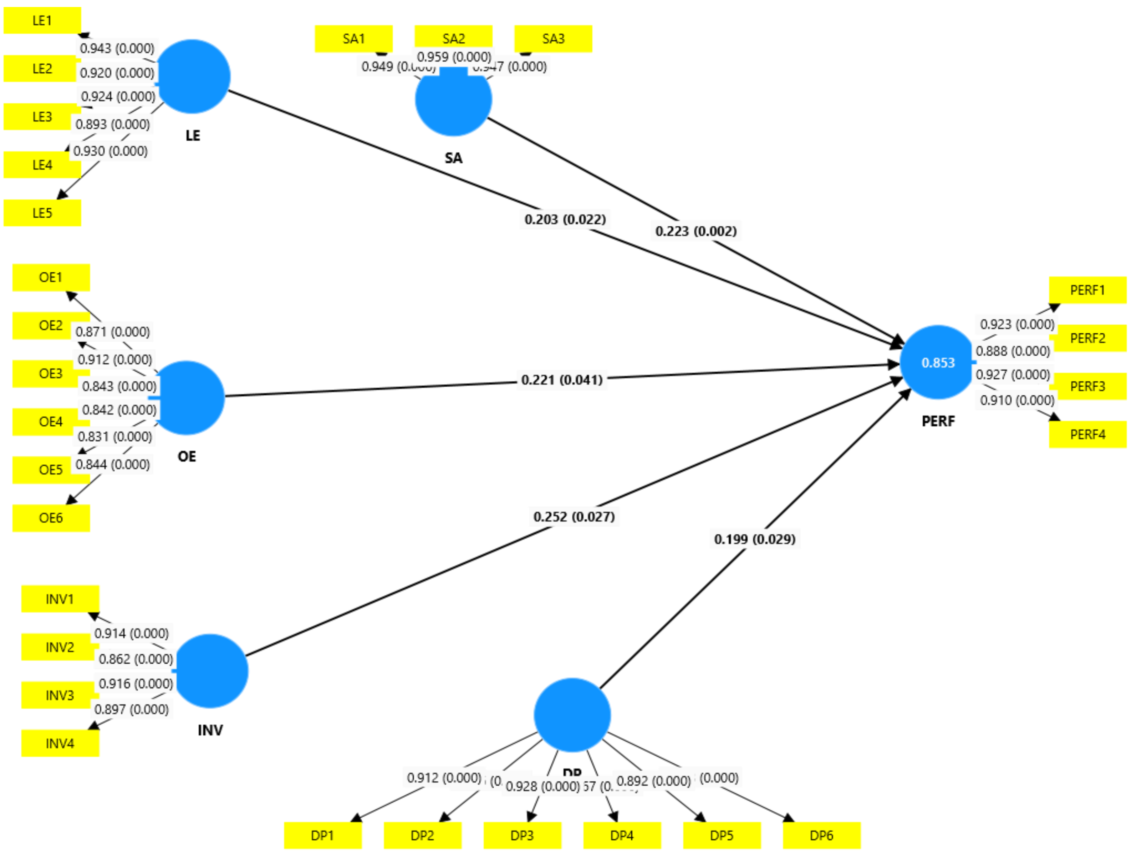


Figure 5.3 Research model gendered by using SmartPLS

Evaluation of the structural model

The path coefficients of PLS structural equation model are presented in Table 5.11.

As shown in the model five factors of competitive advantages namely innovation (β = 0.252), synergistic adaptation (β = 0.223), operating efficiency (β = 0.221), logistics excellence (β = 0.203), disruption preparedness (β = 0.199) are identified in the context of CEP services. The R^2 value shows that the preparedness disruptive environment explains 85.3% of the variance in performance. Hence, H2a, H2b, H2c, H2d, H2e are supported.

Table 5.11 Results of R^2, f^2, and Q^2

Constructs	f^2	R^2	Q^2
DP	0.099		
INV	0.196		
LE	0.104		
OE	0.127		
SA	0.152		
PERF		0.853	0.801

The study model shown robust prediction (Q^2) ability for all the exogeneous construct business performance (see Table). This study intends to evaluate the variation of endogenous components and evaluate the effect size. The f^2 statistic quantifies the influence of a certain external latent variable on an internal latent variable by assessing the variations in the R^2 value (Chin, 1998). Hence, the computation of effect size (Cohen, 1988) resulted in f^2 values of 0.02, 0.15, and 0.35, denoting weak; moderate, and substantial effects, respectively. It is crucial to recognize that a modest f2 value does not necessarily indicate a negligible influence. “Even a small interaction effects can be meaningful under extreme moderating conditions, if the resulting beta changes are meaningful, then it is important to take these conditions into account” (Chin et al., 2003, p.211). Innovation has the highest effect size followed by synergistic adaptation, operating efficiency, logistics efficiency and disruption preparedness in second, third, fourth and fifth place.

5.3.3.2 Model fit indices

Table 5.12 Model Fit

Parameters	*Saturated model*	*Estimated model*	*Thresholds*	*References*
SRMR	0.060	0.060	<=0.08	Hair et al., 2020
NFI	0.706	0.706	>=0.70	Yusif et al., 2020; German et al., 2022
d_ULS	1.479	1.479	p>0.05	Dash & Paul, 2021
d_G	1.144	1.152	p>0.05	Dash & Paul, 2021
GoF	0.565		Small=0.1 Medium= 0.25 Large= 0.36	Sheykhfard et al., 2024; Wasko & Faraj, 2005; Wetzels et al. (2009)
VIF	Between 1 to 5		<=5	Hair et al., 2020; Kock 2015

The fitness analysis involved testing the standardized root mean square residual (SRMR), exact model fit tests (Euclidean distance (d_ULS) and geodesic distance (d_G), and normed fit index (NFI). The SRMR analysis illustrates the disparity between the observed correlation matrix and the anticipated correlation matrix. In the present investigation, the saturated model and estimated model for SRMR were found to be 0.06, suggesting a satisfactory fit, as these values fall below the threshold of 0.08 (Citation). The precise model fit assesses the disparity between an empirical covariance test and the exact model fit. The d_ULS value for the model is 1.479, which is above the threshold of 0.05. In addition, the d_G value for the saturated model is 1.144, whereas the estimated model is 1.152, both of which exceed the significance level of 0.05. This suggests that the model successfully passed the precise model fit tests. According to Bentler and Bonett (1980), values that are closer to 1 in NFI are regarded as having a superior fit. In this investigation, the NFI values for the model are 0.71. These values exceed the threshold of 0.70 (Citation). In general, the model satisfied the statistical fitness criterion, as evidenced by the data presented in Table 5.13.

Goodness of fit: The primary method for assessing the model's explanatory capacity is through the examination of R^2, as Partial Least Squares (PLS) does not yield comprehensive goodness of fit measures (Wasko & Faraj, 2005). However, the Goodness of Fit (GoF) index as a diagnostic tool for assessing the adequacy of model fit was established by Tenenhaus et al. (2005). The GoF measure calculates the geometric mean of the average variance extracted and the average R^2 for endogenous constructs. Sheykhfard et al. (2024) have reported the following threshold values for assessing the outcomes of the GoF analysis: smaller = 0.1, moderate = 0.25, and significant = 0.36. The determined GoF value of 0.703 in this study indicates that the model is highly well-fitting, as stated in Eq. (15).

$$GoF = \sqrt{AVE * R^2} \qquad \dots (15)$$

5.4 Summary

This chapter discusses objective 2 related to the identification of competitive advantage factors. It reveals five factors, namely logistics excellence, operating efficiency, innovation, synergistic adaptation, and disruption preparedness. The PLSSEM analysis shows that innovation is the most significant factor influencing business performance, highlighting its role in driving adaptability and customer-focused improvements during disruptions. Disruption preparedness is found to be the least influential; thus, firms need to focus on the anticipation and mitigation of disruptions for better maintenance of performance during disruptions.