CHAPTER 4

DATA ANALYSIS AND FINDINGS

4.1 Introduction

The five sections in the body of this chapter presents details and elaborations of the findings. The first section presents a descriptive analysis on the demographic information of the survey respondents and the overall response rate. The second section presents an assessment of the reflective measurement model in the Structural Equation Modeling (SEM), elaborating on the data screening process which includes identification of missing data, as well as tests for normality, outliers, linearity, homoscedasticity and multi-collinearity. The third section presents the results of the confirmatory factor analysis which include i) pooled confirmatory factor analysis (CFA) or the goodness of fit of the measurement model in terms of unidimensionality, validity, and reliability and ii) structural model for hypotheses testing. The fourth section discusses the multi group analysis to test the moderating effect of trust on the variables, and the chapter ends with a discussion on the final structural model for the study and the conclusion.

4.2 Descriptive Analysis

This section presents a descriptive analysis of the respondents' demographic information as well as discusses the overall response rate. The study's respondents are 352 employees from 26 toll concessionaire companies in Malaysia.

4.2.1 Demographic Information

Table 4.1 shows the distribution of the respondents who participated in this study explained using two demographic features – level of management and working experience (number of years). In this regard, 162 respondents (46.1%) were from the top management, while 190 respondents (53.9%) were from middle management employees. The majority of respondents (63.9%) had over 11 years working experience, 20.5% had 6 to 10 years working experience, and the remaining 15.6% who had less than 5 years.

Table 4.1: Distribution of Respondents according to Demographics (n=352)

	Frequency	**Percentage (%)**
Management Level		
Top Management	162	46.1
Middle Management	190	53.9
Working Experience		
More than 11 years	225	63.9
Between 6 – 10 years	72	20.5
Less than 5 years	55	15.6

4.2.2 Response Rate

In compliance with data collection requirements, 400 questionnaires were administered to 400 employees as described in 4.2.1 above. From the 400, 352 questionnaires were returned and completed. The response rate was thus 88%, which matched the required response rate for a survey exercise.

Table 4.2: Survey Response Rate

Survey Administered	**Survey Returned**	**Complete Match**
400 **(100%)**	**352**	**352** **(88%)**

4.3 Assessment of the Reflective Measurement Model in Structural Equation Modeling (SEM)

An assessment of the reflective measurement model in SEM was conducted using AMOS Version 23.0. The process started with data screening, including identification of missing data, followed by testing of statistical assumptions such as multivariate normality, detecting outliers, linearity, homoscedasticity, and multi-collinearity between constructs. Hair et al., (2010) quoted that it is vital to test statistical assumptions to avoid violations that may jeopardise the validity of the results.

4.3.1 Data Screening

Various methods were used for data screening including detecting missing values and outliers, conducting normality, linearity and homoscedasticity tests, and checking for multi-collinearity.

4.3.2 Missing Data

Sekaran and Bougie (2010) states that missing data in any research is a serious issue as it can significantly affect the survey's results. In this study, the survey was conducted online, and there were no missing values among the 352 responses.

4.3.3 Multivariate normality

A normality assessment is conducted evaluate the skewness for every variable, and was undertaken using the skewness and kurtosis. A skewness value of 1.0 or lower means the data was normally distributed. The AMOS SEM using the Maximum

Likelihood Estimation (MLE) is a relatively vigorous test to identify skewness more than 1.0 in absolute value, especially in cases with large sample size. Meanwhile, the Critical Region (CR) for the skewness does not exceed 8.0. In MLE, a sample size greater than 200 is considered large even though the data distribution is slightly abnormal.

Therefore, with a sample size greater than 200, the researcher was able to proceed with the analysis with the absolute skewness up to 1.5 (Zainudin, 2015). For this study, the skewness range is -1.164 to -0.499, which is below than the stipulated +-1.5 (Hair et al., 2010), as seen in Table 4.3. Therefore, normality for this data is achieved.

Table 4.3: Assessment of Normality

VARIABLE	MIN	MAX	SKEW	C.R.	KURTOSIS	C.R.
INV1	1.000	5.000	-.499	-3.820	.675	2.583
INV2	1.000	5.000	-.586	-4.490	.590	2.258
INV3	1.000	5.000	-.676	-5.180	1.214	4.648
INV4	1.000	5.000	-.653	-5.002	.824	3.154
INV5	1.000	5.000	-.879	-6.729	1.738	6.655
INV6	1.000	5.000	-.651	-4.989	1.276	4.886
BI1	1.000	5.000	-.619	-4.743	.943	3.613
BI2	1.000	5.000	-.656	-5.025	1.490	5.706
BI3	1.000	5.000	-.556	-4.257	.463	1.773
BI4	1.000	5.000	-.629	-4.819	.606	2.320
BI5	1.000	5.000	-.719	-5.508	.985	3.773
PV1	1.000	5.000	-.717	-5.492	.516	1.977
PV2	1.000	5.000	-.895	-6.853	1.890	7.238
PV3	1.000	5.000	-.662	-5.069	.998	3.820
PV4	1.000	5.000	-.815	-6.245	1.483	5.680

VARIABLE	MIN	MAX	SKEW	C.R.	KURTOSIS	C.R.
PV5	1.000	5.000	-.774	-5.928	1.456	5.577
PV6	1.000	5.000	-.660	-5.054	1.211	4.640
PV7	1.000	5.000	-.798	-6.110	1.120	4.287
PV8	1.000	5.000	-.742	-5.682	.360	1.378
GI6	1.000	5.000	-.865	-6.625	1.214	4.649
GI7	1.000	5.000	-.653	-4.998	.229	.879
GI8	1.000	5.000	-.628	-4.808	.488	1.870
GI9	1.000	5.000	-.832	-6.372	.744	2.849
GI0	1.000	5.000	-.804	-6.157	1.087	4.162
GI11	1.000	5.000	-.888	-6.804	.993	3.804
ATT1	1.000	5.000	-1.164	-8.916	2.657	10.175
ATT2	1.000	5.000	-.533	-4.085	1.804	6.910
ATT3	1.000	5.000	-.796	-6.097	1.506	5.766
ATT4	1.000	5.000	-1.150	-8.810	2.943	11.271
ATT5	1.000	5.000	-.997	-7.638	2.398	9.183
ATT6	1.000	5.000	-.991	-7.592	2.281	8.735
ATT7	1.000	5.000	-1.084	-8.306	2.338	8.954
SN1	1.000	5.000	-.764	-5.849	1.109	4.247
SN2	1.000	5.000	-.521	-3.993	1.014	3.881
SN3	1.000	5.000	-.530	-4.061	.950	3.640
SN4	1.000	5.000	-.708	-5.420	1.230	4.710
SN5	1.000	5.000	-.664	-5.084	1.015	3.886
PBC1	1.000	5.000	-.754	-5.774	.724	2.773
PBC2	1.000	5.000	-.623	-4.772	.533	2.042
PBC3	1.000	5.000	-.881	-6.744	1.222	4.680
PBC4	1.000	5.000	-.626	-4.794	.629	2.410
PBC5	1.000	5.000	-.625	-4.791	.408	1.563
PBC6	1.000	5.000	-.638	-4.884	.555	2.127
PBC7	1.000	5.000	-.618	-4.735	.389	1.488
Multivariate					790.320	116.526

4.3.4 Outliers

Byrne (2010) refers to outliers as any observation that is numerically different in comparison with the overall dataset. Schumacher & Lomax, (1996) state that outliers have the ability to affect the parameter estimates. Table 4.4 shows 43 cases (where squared Mahalanobis distance values exceed the critical chi-square value, which in this case is 73.402 (refer Appendix 1), and are thus considered outliers.

Table 4.4: Outliers

Observation number	Mahalanobis d-squared	p1	p2
335	195.263	.000	.000
261	184.676	.000	.000
248	178.504	.000	.000
97	175.251	.000	.000
247	158.798	.000	.000
141	132.102	.000	.000
234	130.662	.000	.000
81	119.898	.000	.000
228	118.890	.000	.000
3	118.422	.000	.000
242	116.703	.000	.000
292	112.484	.000	.000
260	109.863	.000	.000
294	104.730	.000	.000
274	100.369	.000	.000

Observation number	Mahalanobis d-squared	p1	p2
100	98.458	.000	.000
101	98.458	.000	.000
332	96.188	.000	.000
282	93.797	.000	.000
352	93.797	.000	.000
166	93.196	.000	.000
21	92.236	.000	.000
305	91.856	.000	.000
6	91.746	.000	.000
227	91.095	.000	.000
263	88.344	.000	.000
90	87.056	.000	.000
146	86.591	.000	.000
236	85.720	.000	.000
201	85.383	.000	.000
14	84.864	.000	.000
91	84.730	.000	.000
229	83.970	.000	.000
73	82.534	.000	.000
74	82.261	.000	.000
185	80.855	.001	.000
240	80.666	.001	.000
259	80.557	.001	.000

Observation number	Mahalanobis d-squared	p1	p2
223	**79.380**	**.001**	**.000**
235	**78.577**	**.001**	**.000**
23	**76.710**	**.002**	**.000**
43	**76.697**	**.002**	**.000**
103	**76.681**	**.002**	**.000**
94	72.944	.004	.000
217	72.593	.004	.000
218	71.748	.005	.000

According to Pallant (2011), prior to coming to a decision to maintain or delete the value, the researcher is required to look into Cook's Distance value to identify whether those values (cases) have any unjustified influence on the results. Tabachnick and Fidell, (2007), however, added the cases with Cook's Distance value of larger than 1 are those found to have potential problems. In the case of this study, the Cook's Distance value, seen in Table 4.5, shows a maximum value is 0.822 (less than 1). Based on this, all 43 cases were retained (Pallant, 2011).

Table 4.5: Cook's Distance Value

	Min.	Max.	Mean	Standard Deviation	N
Cook's Distance	.000	.822	.006	.045	352

4.3.5 Linearity and Homoscedasticity

The assessment of linearity was conducted through a residual analysis that resulted from the regression analysis. The homoscedasticity test was conducted using a scatter plot diagram of standardised residuals, and results showed the existence of homoscedasticity in the set of independent variables, and the variance of the dependent variable.

Pallant (2011) assumptions of linearity and homoscedasticity can be identified by examining a scatter plot of standardised residuals. Figure 4.1 shows the scatter plot for linearity and homoscedasticity scores are concentrated in the centre (along with the 0 points). Therefore, the linearity and homoscedasticity are achieved for this data.

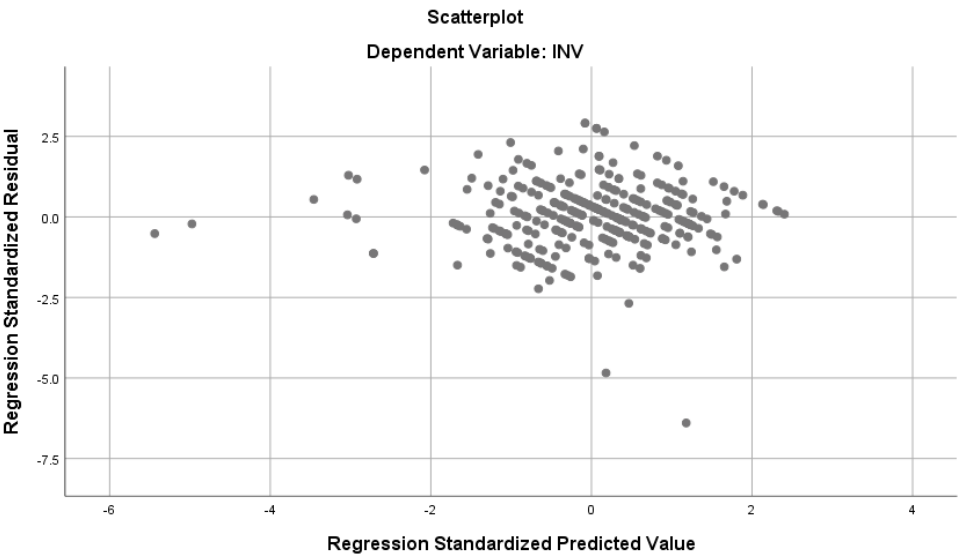

Figure 4.1: Scatter plot of the Standardised Residuals

4.3.6 Multi-collinearity

Multi-collinearity can be defined as the component variables being close equal in linearity (Zainuddin, 2015). Multi-collinearity is basically when two or more variables are not independent and is seen as simply a matter of identifying the degree of closeness, to allow proper treatment to be taken in the study. When variables are used as predictors, a sufficiently high degree of interdependence can render the model results inadequate and misleading.

As such, the Structural Equation Modeling (SEM) is a powerful method for managing multi-collinearity in sets of predictor variables. The importance of multi-collinearity is to define the correlation value between variables where a value not exceeding 0.85 shows that the variable is free from the redundant items (Zainudin, 2015).

Table 4.6: Correlation Matrix

	PBC	SN	ATT	GI	PV	BI	INV
Perceived Behavioural Control (PBC)	-						
Subjective Norm (SN)	.697	-					
Attitude (ATT)	.566	.623	-				
Governmental Influence (GI)	.543	.559	.486	-			
Project Viability (PV)	.611	.615	.601	.656	-		
Behavioural Intention (BI)	.635	.590	.542	.607	.586	-	
Involvement (INV)	.592	.609	.595	.567	.682	.588	-

Multi-collinearity occurs when the correlation matrix between any two variables show an extremely high value, i.e. a value of above 0.85 for any variable is deemed as a redundant variable (Zainudin, 2015). Table 4.6 shows the value for perceived behavioural control, subjective norm, attitude, governmental influence, project viability, behavioural intention and involvement variables are between 0.486 to 0.697, where the correlation among all the variable is below 0.85 and thus indicating that there are no redundant items between variables.

4.4 Hypothesis Testing

This section will be present on the results and analysis of the hypotheses tested for this study, which predominantly uses the SEM methods. In this study, four stages of analysis were used:

i. Measurement Model;
ii. Structural Model; and
iii. Multi Group Analysis, which is used to determine the moderation effects of the trust between behavioural intention and involvement behaviour.

4.4.1 Measurement Model

This section explains the process of analysing data using the Confirmatory Factor Analysis (CFA) method. This includes the processes of assessing measurement validity, uni-dimensionality and reliability. Prior to modelling the structural model and executing SEM, the study is first required to validate all latent constructs involved in the model (Zainudin, 2015). This validation procedure is known as CFA, which can be executed using two methods – the single construct CFA and the Pooled-CFA for all constructs.

This study utilises the Pooled-CFA method as it is seen to be more suitable, efficient and thorough, as well as able to avoid any model identification problems, as indicated by Zainudin (2015). Under Pooled-CFA, all the constructs are pooled together and linked using the double-headed arrows to assess the correlation among them. In this case, all the constructs were pooled and assessed simultaneously.

The seven variables of this study – perceived behavioural control, subjective norm, attitude, governmental influence, project viability, behavioural intention and involvement – which can be further broken down into 44 items is shown in Figure 4.2.

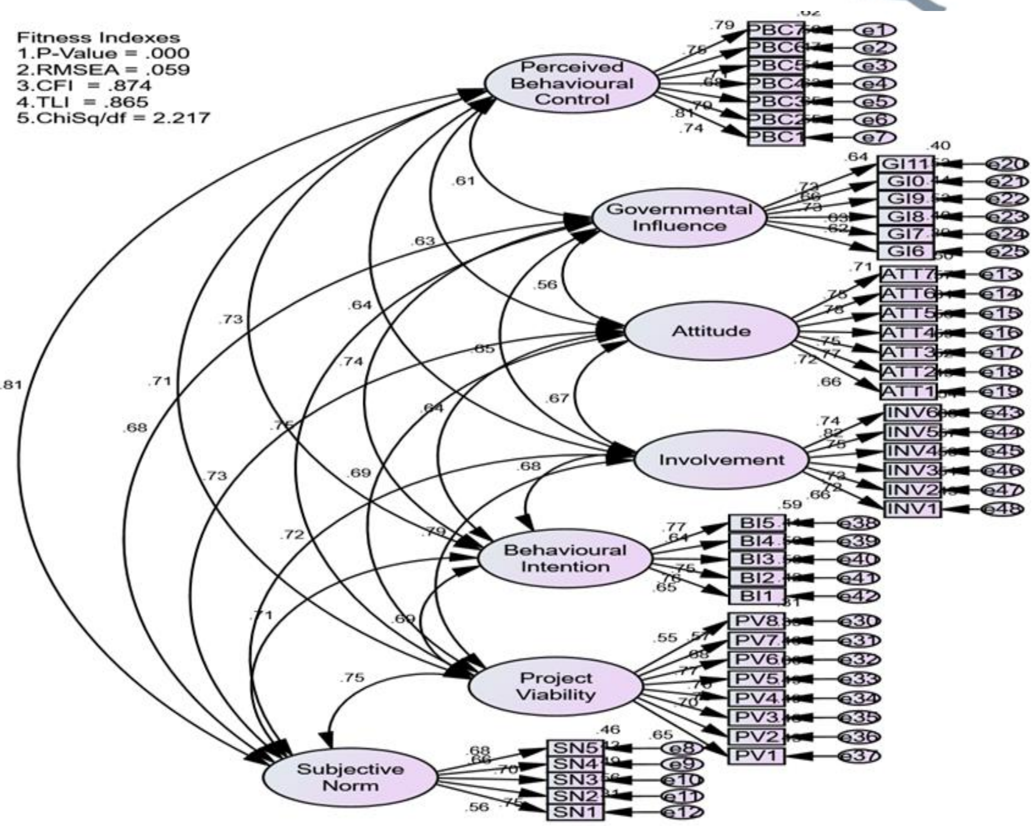

Figure 4.2: Pooled-CFA

Three assessments for (i) unidimensionality; (ii) validity; and (iii) reliability for measurement models, were required before modelling the structural model. These assessments are explained below:

(i) Unidimensionality

The requirement of fitness indexes for this study was achieved through item-removal of low factor loading items identified through pooled-CFA. Eight items were deleted – three from governmental influence (G6, G7, G11); two from subjective norm

(SN1, SN4); and three under project viability (PV1, PV7, PV8), after which, the model run and the fitness indexes achieved the required levels for the study to continue (Figure 4.3).

The fitness indexes were met based on requirements specified by Hair, et al. (2010). There was no issue of Model Identification in this study event with the removal of the eight constructs since the combined constructs would have increased the degrees of freedom for the model (Zainudin, 2015). On a similar note, all items showed positive factor loading values.

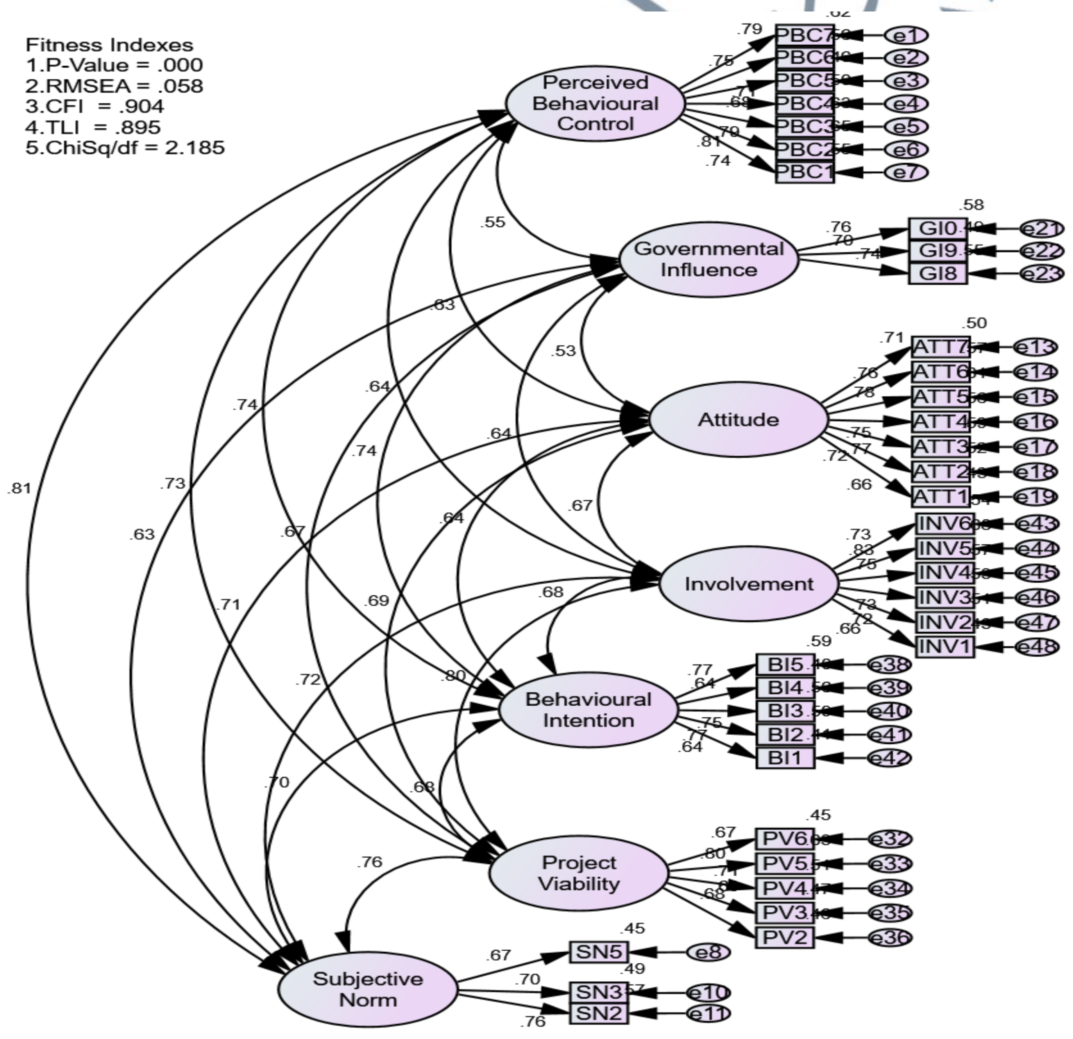

Figure 4.3: The Pooled-CFA after Removal of Low Loading Items

(ii) Validity

For validity assessment, three processes were conducted, namely:

a. convergent validity;

b. construct validity; and

c. discriminant validity.

(a) *Convergent Validity* - The assessments for Convergent Validity was made based on the values of Average Variance Extracted (AVE) and Composite Reliability (CR) as shown in Table 4.7. The study computed these values for every construct, with a minimum threshold value for AVE is 0.5 or higher, and CR is 0.6 identified for validity to be achieved (Hair et al., 2010).

Table 4.7: The AVE and CR Values for all Constructs

Construct	**Item**	**Factor Loading (above 0.50)**	**CR (above 0.6)**	**AVE (above 0.5)**
Perceived Behavioural Control	PBC1	.74	0.902	0.569
	PBC2	.81		
	PBC3	.79		
	PBC4	.71		
	PBC5	.68		
	PBC6	.75		
	PBC7	.79		
Subjective Norm	SN1	**Removed**	0.754	0.506
	SN2	.76		
	SN3	.70		
	SN4	**Removed**		
	SN5	.67		
Attitude	ATT1	.66	0.892	0.543
	ATT2	.72		

Construct	Item	Factor Loading (above 0.50)	CR (above 0.6)	AVE (above 0.5)
	ATT3	.77		
	ATT4	.75		
	ATT5	.78		
	ATT6	.76		
	ATT7	.71		
Governmental Influence	GI11	**Removed**	0.778	0.538
	GI10	.76		
	GI9	.70		
	GI8	.74		
	GI7	**Removed**		
	GI6	**Removed**		
Project Viability	PV1	**Removed**	0.836	0.506
	PV2	.68		
	PV3	.69		
	PV4	.71		
	PV5	.80		
	PV6	.67		
	PV7	**Removed**		
	PV8	**Removed**		
Behavioural Intention	BI1	.64	0.840	0.514
	BI2	.77		
	BI3	.75		
	BI4	.64		
	BI5	.77		
Involvement	INV1	.66	0.877	0.545
	INV2	.72		
	INV3	.73		
	INV4	.75		
	INV5	.83		
	INV6	.73		

The results in Table 4.7 show the AVE and CR values for all constructs exceeds the threshold value of 0.5 and 0.6 respectively. Thus, the study concludes that the Convergent Validity and Composite Reliability for all constructs in the model have been achieved (Zainudin, 2015).

(b) *Construct Validity* - From the Pooled-CFA results, the researcher intended to identify the Fitness Indexes for the measurement model, the factor loading for each item, and the correlation between constructs.

Table 4.8: Fitness Indexes for Fitness of the Constructs

Name of category	Name of index	Index value	Comments
1. Absolute fit	RMSEA	0.058	Required level achieved
2. Incremental fit	CFI	0.904	Required level achieved
3. Parsimonious fit	ChiSq/df	2.185	Required level achieved

Table 4.8 shows that the required values for the Fitness Indexes have been achieved for Construct Validity as proposed by Zainudin (2012). Based on this, the measurement model is said to have achieved Construct Validity.

(c) *Discriminant Validity* - The final step of the Pooled-CFA method, the study assessed the discriminant validity of the constructs to clarify that they are not redundant of each other. Discriminant validity for the construct is achieved if the correlation among the independent variable in the model does not exceed 0.85 (Zainudin, 2015). The study also developed a Discriminant Validity Index Summary (Table 4.9) for all constructs in the model.

Table 4.9: Discriminant Validity Index Summary

	PBC	SN	ATT	GI	PV	BI	INV
Perceived Behavioural Control (PBC)	**.754**						
Subjective Norm (SN)	.697	**.711**					
Attitude (ATT)	.566	.623	**.736**				
Governmental Influence (GI)	.543	.559	.486	**.733**			
Project Viability (PV)	.611	.615	.601	.656	**.711**		
Behavioural Intention (BI)	.635	.590	.542	.607	.586	**.716**	
Involvement (INV)	.592	.609	.595	.567	.682	.588	**.738**

The diagonal values in bold presented in Table 4.9 are the square root of the AVE of the respective constructs, while other values are the correlation between the respective pair of constructs. The Discriminant Validity of the particular construct is achieved if the square root of its AVE exceeds its correlation value with other constructs in the model. In other words, the discriminant validity is achieved if the diagonal values (in bold) are higher than any other values in its row and column.

Based on these criteria, and looking at the tabulated values in Table 4.9, the study meets the threshold of discriminant validity. Thus, the study concludes that the Discriminant Validity for all constructs is achieved.

(iii) Reliability

Reliability is the extent of how reliable the said measurement model is in measuring the proposed latent construct. The assessment for reliability for a measurement model uses the following criteria: -

a) *Composite Reliability* (CR) – The CR indicates the reliability and internal consistency of a latent construct. A CR value of 0.6 or higher is required in order to achieve composite reliability. Table 4.6 shows the CR value for the constructs perceived behavioural control (0.902), subjective norm (0.754), attitude (0.892), governmental influence (0.778), project viability (0.836), behavioural intention (0.840) and involvement (0.877). As such, all the constructs achieve the required CR.

b) *Average Variance Extracted* (AVE) – The AVE value indicates the average percentage of variation explained by measuring the items for a latent construct. An AVE of at least 0.5 is required for every construct. Table 4.6 shows the AVE for constructs perceived behavioural control (0.569), subjective norm (0.506), attitude (0.543), governmental influence (0.538), project viability (0.506), behavioural intention (0.514) and involvement (0.545). Based on this, all the constructs have achieved the requirement of AVE.

4.4.2 Structural Model

This section explains the process of analysing data using the Confirmatory Factor Analysis (CFA) method. This includes the processes of assessing measurement validity, uni-dimensionality and reliability. Prior to modelling the structural model and executing SEM, the study is first required to validate all latent constructs involved in the model (Zainudin, 2015). This validation procedure is known as CFA, which can be executed using two methods – the single construct CFA and the Pooled-CFA for all constructs.

The section illustrates the process of answering the research objectives and research questions that have been earlier presented in Chapter 1, mainly those related to the use of SEM analysis. After confirming the validity of the measurement model, the structural model is specified as by assigning relationships between the constructs based on the conceptual framework developed in Chapter 2 (Figure 4.4). The following hypotheses were then tested:

H1: *The decision makers' attitude has a positive effect on their behavioural intention towards involvement in PPP toll expressway projects*.

H2: *Subjective norms have a positive effect on the behavioural intention of the decision makers in the private sector towards invovement in PPP toll expressway projects*.

H3: *Perceived behavioural control has a positive effect on the behavioural intention of the decision makers in the private sector towards involvement in PPP toll expressway projects*.

H4: *Governmental influence has a positive effect on the behavioural intention of the decision makers in the private sectors towards involvement in PPP toll expressway projects*.

H5: *Project viability has a positive effect on the behavioural intention of the decision makers in the private sectors in PPP toll expressway projects*.

H6: The behavioural intention of the decision makers in the private sector has a positive effect on their involvement behaviour in PPP toll expressway projects.

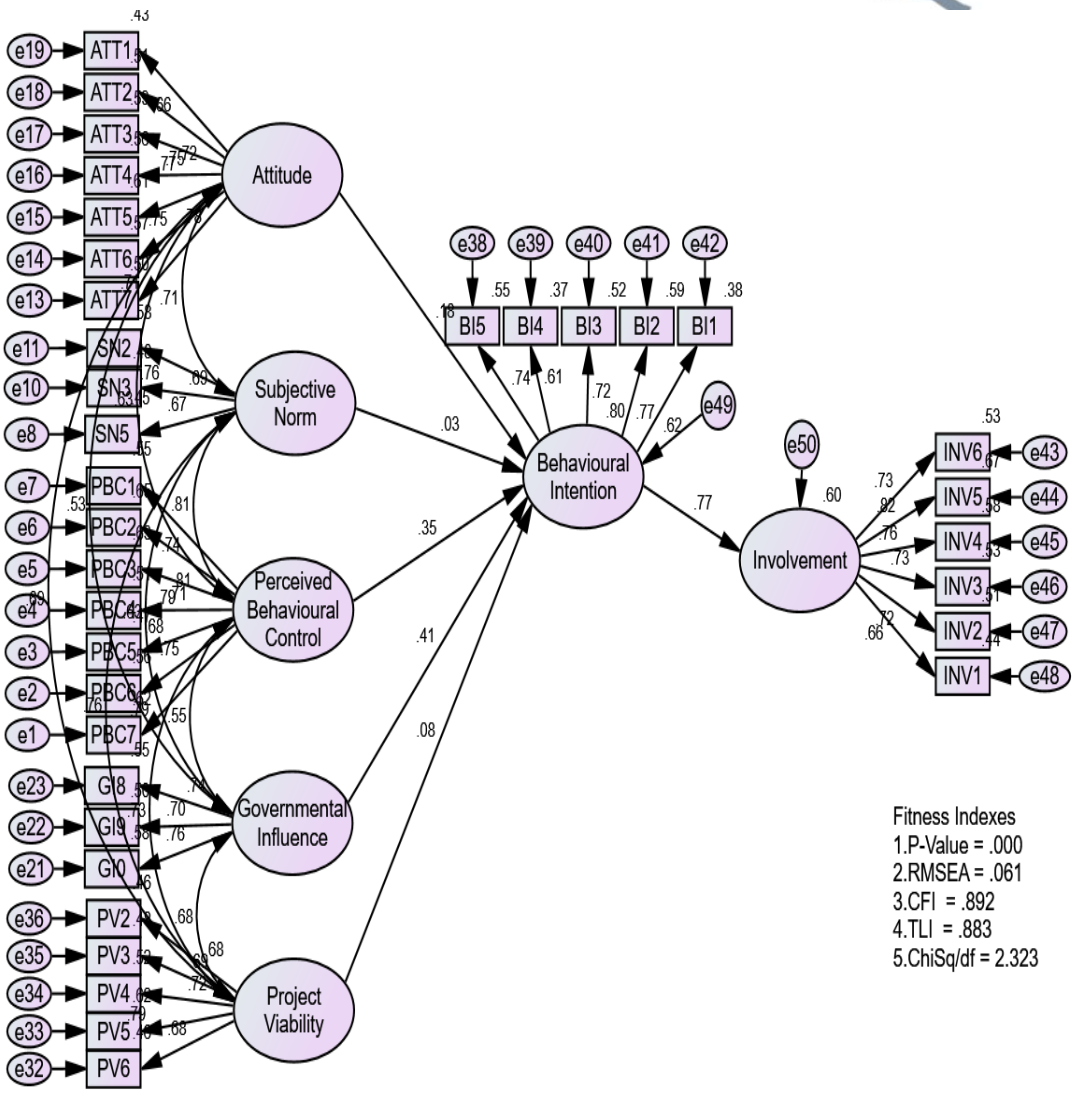

Figure 4.4: Structural Model

The results displayed within Table 4.9 affirms that attitude, perceived behavioural control, government influence contribute significantly to behavioural intention and behavioural intention significantly impact on involvement. Meanwhile, subjective norm and project viability are not significant to behavioural intention.

According to Hair et al (2016), the significance level for p value is below than 0.05 and the critical ratio (CRa) is above 1.96. Governmental influence report the highest contribution (β=0.415, t-value = 5.780 >1.96) followed by perceived behavioural control (β=0.329, t-value = 4.131 > 1.96), and finally attitude (β=0.205, t-value = 2.841 > 1.96) which has a very little bearing on involvement. On the other relationships, behavioural intention contributed significantly to involvement (β=0.657, t-value =11.080 >1.96).

Table 4.10: The Hypotheses Result based on Bootstrapping

H		Estimate (β)	SE	CRa t=value	P	Result
H1	Attitude → Behavioural Intention	.205	.072	2.841	.004	**Supported**
H2	Subjective Norm → Behavioural Intention	.030	.123	.243	.808	**Not Supported**
H3	Perceived Behavioural Control → Behaviour Intention	.329	.080	4.131	***	**Supported**
H4	Governmental Influence → Behavioural Intention	.415	.072	5.780	***	**Supported**
H5	Project Viability → Behavioural Intention	.094	.101	.934	.350	**Not Supported**
H6	Behavioural Intention → Involvement	.657	.059	11.080	***	**Supported**

Therefore, H1, H3, H4 and H6 are supported and H2 and H5 are not supported. Based on these results, the relationship between behavioural intention and involvement is significant. Subsequently, this study proceeded to analyse the moderating effect to address H7, as presented in the following sections.

However, before proceeding to analyse the moderating effect under H7 hypothesis, the author extended an additional exercise of H2 and H5 due to its insignificant result. In clarifying further on these insignificant results of H2 and H5, the interview exercise with few Chief Executive Officer (CeO) of the toll concessionaires' companies have been conducted. Nevertheless, this interview exercise is only to seek clarification in justifying the result, thus content analysis is not required as this interview process is not part of the study.

Due to insignificant result of H2 (subjective norm) and H5 (project viability), the interview with CeO of X, Y and Z company (*undisclosed real name due to privacy reason*) have been conducted and every insignificant construct have been asked a question as follow;

Question 1: "Why do you think subjective norm or significant other is not important element for the company in considering involvement in PPP toll expressway project?"

Answered of Question 1 by CeO of X toll concessionaire:

"In PPP toll expressway business, the third parties neither give much impact nor influence on the consideration of participation, as management team in the companies would work very hard to secure this huge project and looking forward to have long-term contract with the government."

Answered of Question 1 by CeO of Y toll concessionaire:

"In developing country, such as Malaysia, the influences of local society such as non-governmental organisations or association bodies do not jeopardise

much on the company's decision making particularly in deciding to get involve in government contract."

Answered of Question 1 by CeO of Z toll concessionaire:

"*PPP is between the company and government, thus the company should take full consideration and cautioned more on fulfilling obligation between partners rather than too focus on others. Thus, besides stakeholders, others do not much influence in our decision making in PPP*."

<u>Question 2</u>: "Why do you think project viability is not important element for the company in considering involvement in PPP toll expressway project?"

Answered of Question 2 by CeO of X toll concessionaire:

"*Normally the government already took full study on the viability of the PPP project before call for any tender or RFP (request for proposal), thus, in deciding to participate or not, the company more focus on financial feasibility in term of projected revenue rather than overall of project viability*."

Answered of Question 2 by CeO of Y toll concessionaire:

"*By having a concession agreement in PPP, the viability of project would not be the main concern for the company as the profit guaranteed and projected future profit are clearly stipulated in the contract*."

Answered of Question 2 by CeO of Z toll concessionaire:

"We have a very good government and our government policy is a business-friendly policy particularly in lure of private sector's participation and involvement in the public infrastructure projects. Hence, project viability should not be an issue as the company could rely on full government support and assistance especially when the nature of project involves national interest."

4.5 Multiple Group Analysis – Moderation Analysis

Zainudin (2015) emphasises the complexities in analysing the moderating effect for a model with latent construct. The multi-group CFA suggests an alternative method for this process, with two separate models – one is constrained model and the other is an unconstrained model. The path of a constrained model would have a parameter = 1.

This study has adopted the moderation process for multi-group CFA by Zainudin (2015), looking at trust as the moderator variable in the relationship between behavioural intention and involvement behaviour of the private sector in PPP toll expressway projects (H7). This is depicted in Figure 4.5. In testing trust as a moderator, the researcher divided two datasets – high data trust (scale 3.51 to 5.00) and low data trust (scale 1.00 to 3.50). Each dataset was tested using the two models – constrained model and unconstrained model.

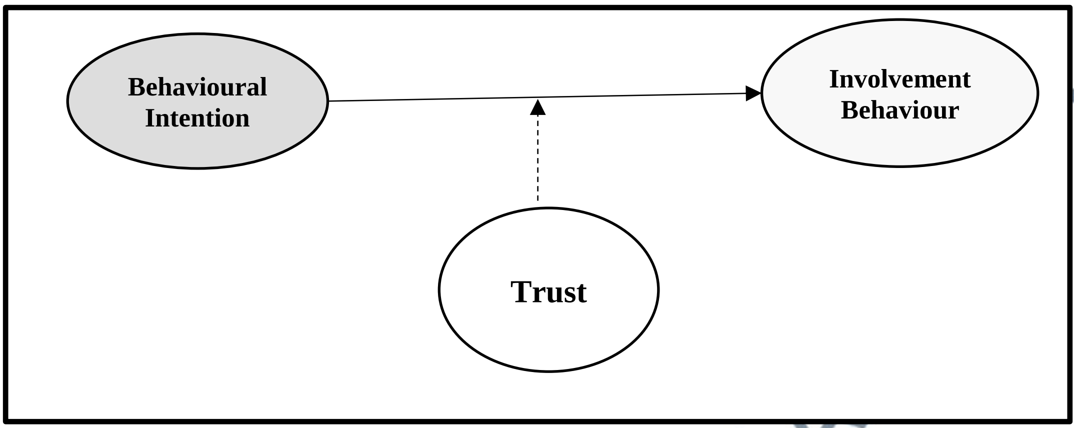

Figure 4.5: Trust as a Moderator

The results of the tests are significant if the difference in Chi-Square value for the constrained and unconstrained model is found to be above 3.84. Two types of moderators, full moderator and partial moderator, were seen. Full moderator occurs when high data or low data is significant, while, partial moderator occurs when both high and low data are significant (Zainudin, 2015). Trust was analysed as a moderator on both tests, high and low data, using constrained and unconstrained model.

4.5.1 Test Moderation for High Data - Trust

In elaborating this test, Figure 4.6 High Trust Data: Outputs for the Constrained Model, Table 4.11 Chi-Square Value and DF for the Constrained Model for High Data Trust, Figure 4.7 High Trust Data: Outputs for the Unconstrained Model, and Table 4.12 Chi-Square Value and DF for the Unconstrained Model for High Data Trust are referred. Further explanation is provided in the following paragraphs.

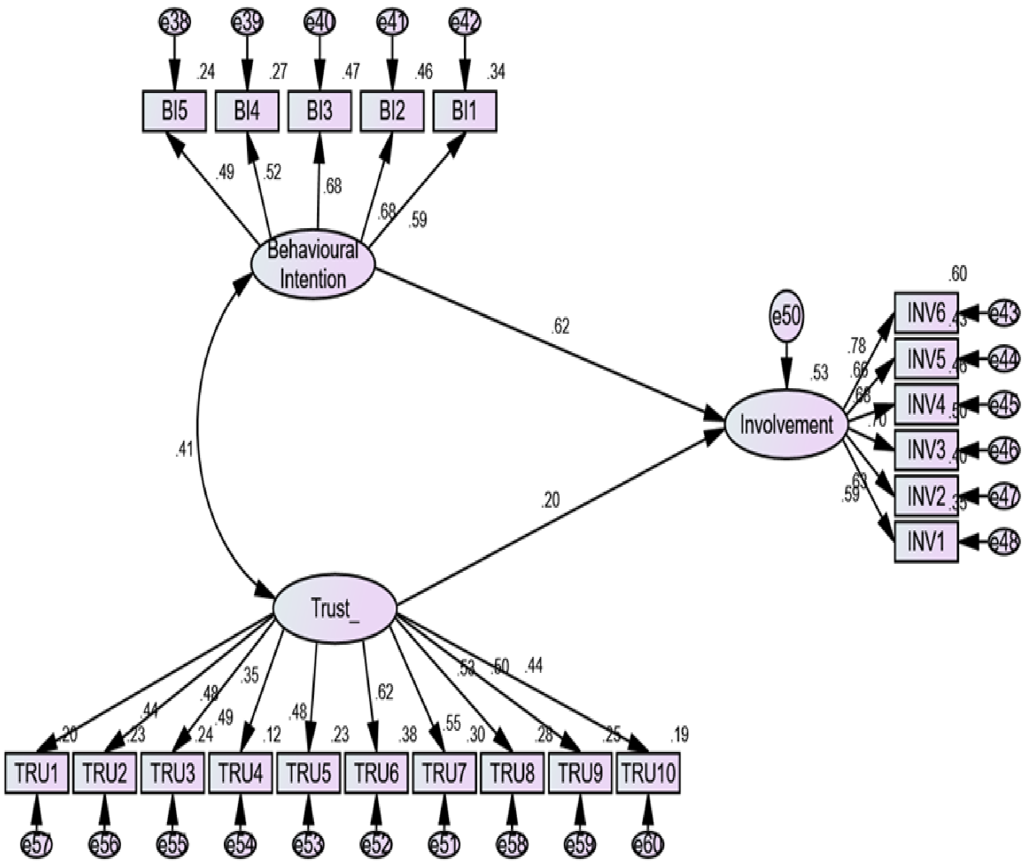

Figure 4.6: High Data Trust: Outputs for the Constrained Model

Table 4.11: Chi-Square Value and DF for the Constrained Model for High Data Trust

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	32	200.056	88	.000	2.273
Saturated Model	120	.000	0		
Independence Model	15	795.408	105	.000	7.575

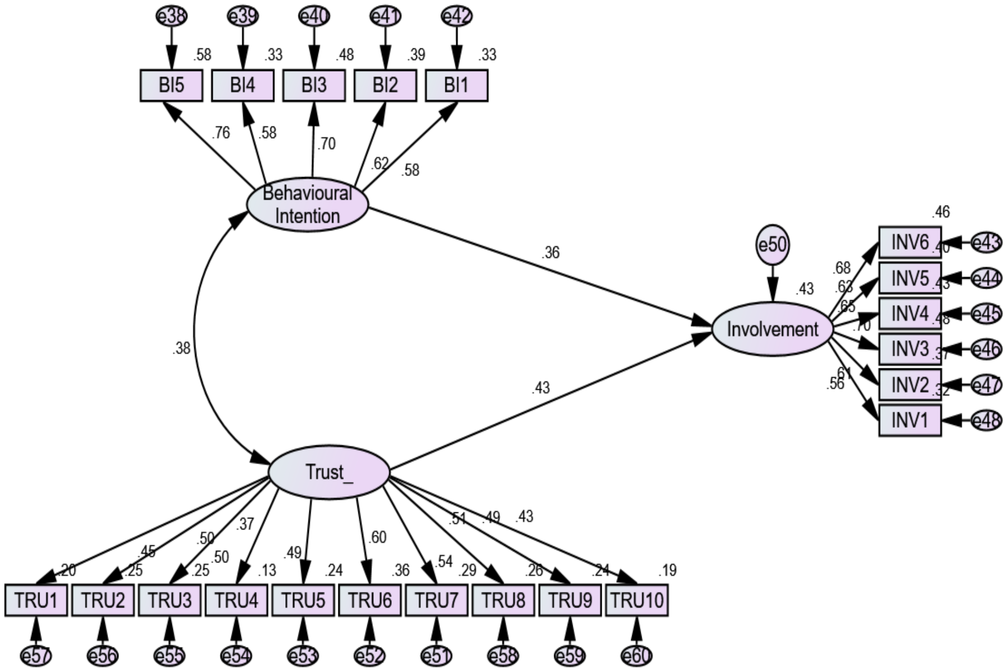

Figure 4.7: High Data Trust: Outputs for the Unconstrained Model

Table 4.12: Chi-Square Value and DF for the Unconstrained Model for High Data Trust

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	33	170.587	87	.000	1.961
Saturated Model	120	.000	0		
Independence Model	15	795.408	105	.000	7.575

Table 4.11 shows the output of chi-square values for the constrained model, where the CMIN is 200.056 and DF is 88. Meanwhile, Table 4.12 shows the output of chi-square values for unconstrained model, where the CMIN is 170.587 and DF is 87.

For the moderators to be significant, the difference in Chi-Square value between constrained model and unconstrained model must be higher than 3.84 with 1 degree of Freedom (Zainudin, 2012). Table 4.13 shows the moderation test for High trust is significant as the difference in Chi-Square value between the constrained (200.056) and unconstrained (170.587) models is 29.469 (200.056-170.587) while the Degree of Freedom is 88-87 = 1.

Table 4.13: The Moderation Test for High Data Trust Results

	Constrained Model	**Unconstrained Model**	**Chi-Square Difference**	**Result on Moderation**
Chi-Square	200.056	170.587	29.469	Significant
DF	88	87	1	

The test carried out for H7 on moderation found that the moderator variable for High trust does have a moderating effect on the relationship between behavioural intention and involvement behaviour as the difference in Chi-Square value is 29.469, which is above the requirement of 3.84.

4.5.2 Test Moderation for Low Data - Trust

In elaborating this test, Figure 4.8 Low Data Trust: Outputs of the Constrained Model, Table 4.13 the Chi-Square Value and DF for the Constrained Model for Low Data Trust, Figure 4.9 Low Data Trust: Outputs for the Unconstrained Model and Table 4.14 the Chi-Square Value and DF for the Unconstrained Model for Low Data Trust are referred. Further explanation is provided in the following paragraphs.

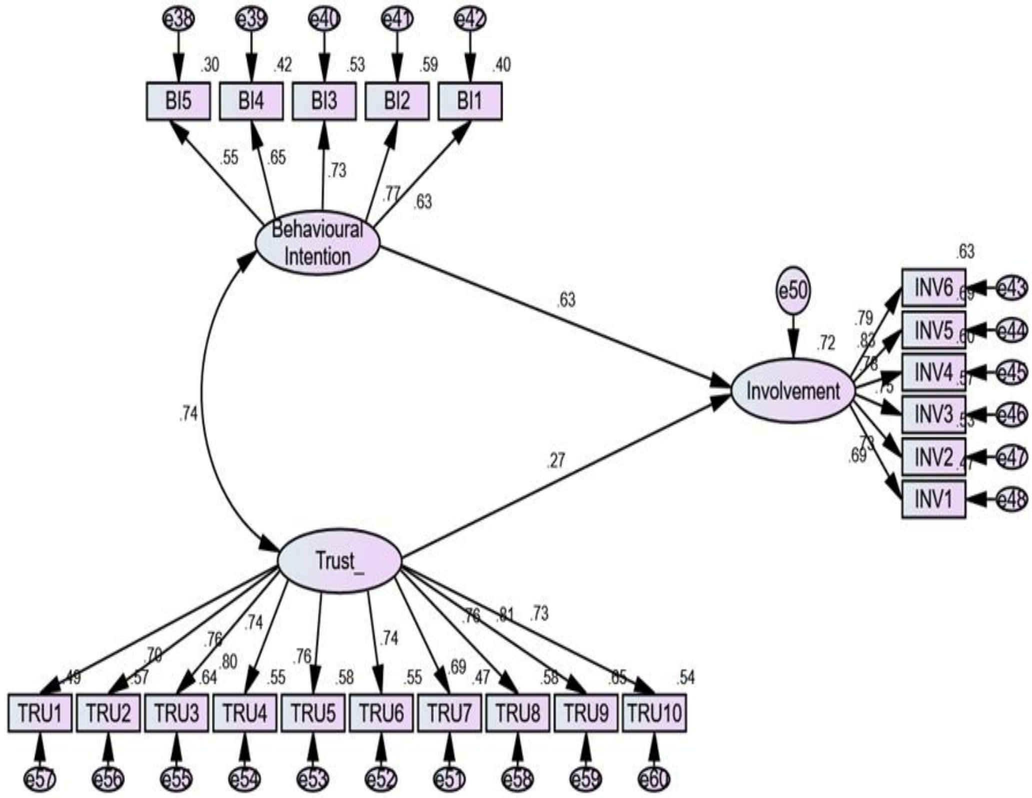

Figure 4.8: Low Data Trust: Outputs for the Constrained Model

Table 4.14: Chi-Square Value and DF for the Constrained Model for Low Data Trust

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	32	291.141	88	.000	3.308
Saturated Model	120	.000	0		
Independence Model	15	2766.463	105	.000	26.347

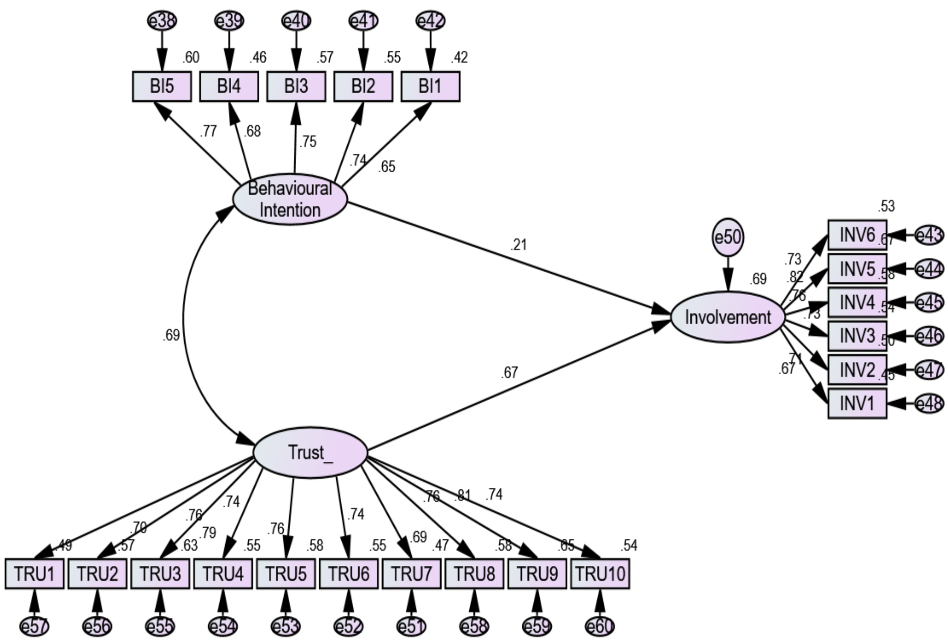

Figure 4.9: Low Data Trust: Outputs for the Unconstrained Model

Table 4.15: Chi-Square Value and DF for the Unconstrained Model for Low Data Trust

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	33	205.258	87	.000	2.359
Saturated Model	120	.000	0		
Independence Model	15	2766.463	105	.000	26.347

Table 4.14 is output of chi-square value for the constrained model, where the CMIN is 291.141 and DF is 88, while, Table 4.15 shows the output of chi-square value for the unconstrained model, where the CMIN is 205.258 and DF is 87. For the test moderation to be significant, the difference in Chi-Square value between the constrained and unconstrained models must be higher than 3.84 with 1 degree of freedom (Zainudin, 2012).

Table 4.16 shows the moderation test for Low Data Trust is significant since the difference in Chi-Square value between the constrained and unconstrained model is 85.883 (291.141-205.258), while the Degree of Freedom (DF) is 88-87 = 1. Thus, the Chi-square value is above than 3.84 and therefore, the low data trust is significant.

Table 4.16: The Moderation Test for Low Data Trust Results

	Constrained Model	Unconstrained Model	Chi-Square Difference	Result on Moderation
Chi-Square	291.141	205.258	85.883	Significant
DF	88	87	1	

The tests for H7 on moderation that has been carried out found that the moderator variable for High and Low trust does have a moderating effect on the relationship between behaviour and involvement. The next step is for this analysis to identify which data group (low trust or high trust) shows a more definite moderator variable (trust) effect. This process requires the standardised estimates for the path of interest for both datasets.

Table 4.17: The Standardised Estimate for High Data Trust

Construct	Standardised Beta Estimate	P	Result
Behavioural Intention → Involvement	.260	.000	Supported

Table 4.18: The Standardised Estimate for Low Data Trust

Construct	Standardised Beta Estimate	P	Result
Behavioural Intention → Involvement	.171	.001	Supported

Based on the results, the standardised beta estimate for high data trust is 0.260 with the P value 0.000 (Table 4.17) and for low data trust is 0.171 with the P value 0.001(Table 4.18). As such, it can be concluded that the effect of the moderation is supported in both high trust and low trust. The results also show that the type of moderation is partial moderation as the standardised estimates for both high data trust and low data trust are significant. In conclusion, H7 is supported where trust is confirmed as a partial moderator in the relationship between behavioural intention and involvement.

4.6 Final Structural Model

Figure 4.10 shows the critical ratio and followed by p value for the Final Structural Model. The critical ratio indicates the level of factor loading, where a minimum critical ratio value of 1.960 is required for it to be considered significant (Byrne, 2010). Meanwhile, a p value of below 0.05 is considered to be significant.

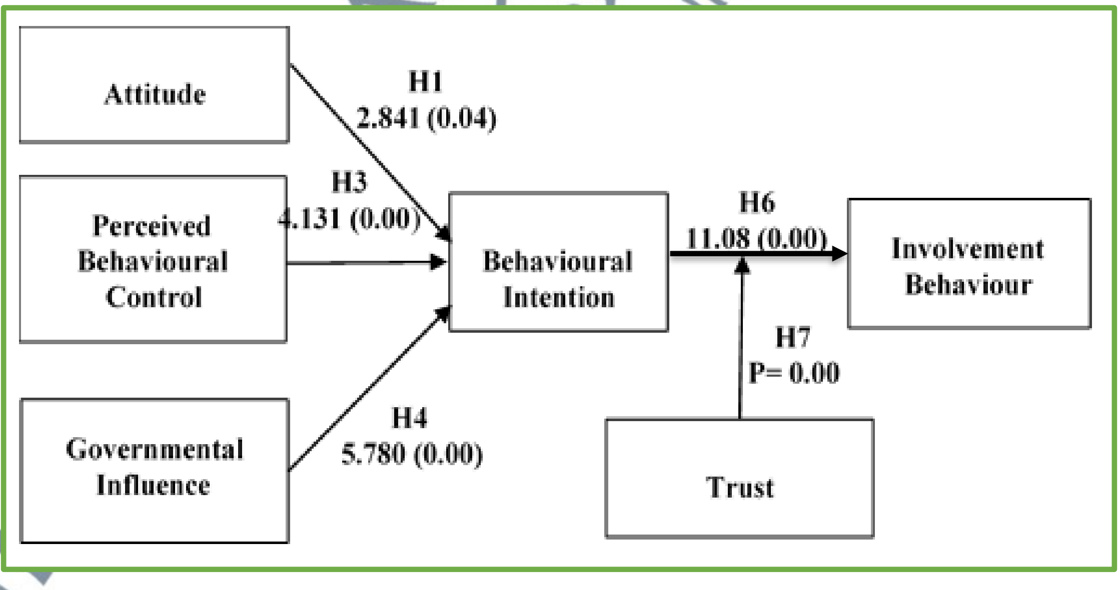

Figure 4.10: Final Structural Model

Table 4.19 shows the summary of seven hypotheses of this study. The results for each hypothesis are as follow: H1, H3, H4, H6 and H7 are ssupported and H2 and H5 are not supported.

Table 4.19: Summary of Hypotheses

Hypothesis	Statement	Result
H1	*The decision makers' attitude has a positive effect on their behavioural intention towards involvement in PPP toll expressway projects.*	**Supported**
H2	*Subjective norms have a positive effect on the behavioural intention of the decision makers in the private sector towards invovement in PPP toll expressway projects.*	**Not Supported**
H3	*Perceived behavioural control has a positive effect on the behavioural intention of the decision makers in the private sector towards involvement in PPP toll expressway projects.*	**Supported**
H4	*Governmental influence has a positive effect on the behavioural intention of the decision makers in the private sectors towards involvement in PPP toll expressway projects.*	**Supported**
H5	*Project viability has a positive effect on the behavioural intention of the decision makers in the private sector towards involvement in PPP toll expressway projects..*	**Not Supported**
H6	*The behavioural intention of the decision makers in the private sector has a positive effect on their involvement behaviour in PPP toll expressway projects.*	**Supported**
H7	*Trust has a moderating effect on the relationship between behavioural intention and involvement behaviour in PPP toll expressway projects*	**Supported**

4.7 Conclusion

This chapter presents in detail the findings of this study. Overall, the response rate to the survey conducted was good and focused, with 88 per cent of respondents strictly from toll concessionaire companies in Malaysia. The respondents also show a balanced ratio between middle and top management employees, with the majority of them having over 11 years working experience.

The data screening process was conducted to remove the outliers, confirm normality as well as to check for multi-collinearity. Confirmatory factor analyses were conducted to ensure construct validity of all variables. Reliability tests were conducted to determine the internal consistency between items and minimise random errors. On top of that, discriminant validity assessment was done to provide an additional measure for all remaining items.

This chapter also presented the results of the hypotheses tests, effect of the moderator, and the outcome of the structural equation models. The results, in general, supported most of the hypotheses, except subjective norms and project viability. The study's overall results and recommendations will be discussed in greater detail in the next chapter.