CHAPTER 5 Data Analysis and Results

Preview

This chapter provides a detailed account of the statistical tests used to test the proposed hypothesis for the study. The preliminary information about the data is presented in the descriptive statistics section and further sections cover the advance statistical methods for generating inferences. The proposed model is a union of two major theoretical frameworks (i.e., UTAUT2 and TTF) with the inclusion of an additional construct on perceived security (refer to chapter 3 for a detailed description). Section 5.2 gives a brief overview of the pls algorithm and how it is used in the study. Section 5.3- 5.5 are the necessary evaluation methods before applying the pls algorithm to the proposed model. The next section is on the evaluation of the model and how well it can describe the explained variance of the adoption phenomenon. Section 5.7 measures the difference in perception based on the demographic variables through multigroup analysis and the subsequent section describes the effect of government policy on the adoption behavior through moderator analysis. The final section describes how well the constructs performed vis-à-vis their perceived importance.

5.1. Descriptive Statistics

This study has used survey-based methods to collect data. 1250 questionnaires were distributed, and 932 responses (74.5% response rate) were filled and returned. Similar response rates of 70 % and 66% were found by the studies conducted by Alalwan et.al (2018) and Gupta et.al (2019) respectively. The dataset was further checked for incomplete responses and suspicious response patterns. A question was also included to check whether the respondent was paying attention or not. During this process, 402 responses were removed. Finally, 30 additional responses were removed as these individuals were nonusers of mobile payment to avoid class imbalance problem during analysis. The final usable dataset is of 500 cases which represents the users of mobile payment. Age, Gender, Education and Income were included as demographic indicators. The sample population consists of 62.2% male and 37.8% female. The majority of the individuals fall into the age category of 20-29 (43.3%), followed by 30-39 (29.2%), 40-49 (14.6%) and a small percentage of the sample belonged to the age group of 50-59(5%), greater than the age of 60(2%) and finally the age group of less than 20 (5.4%). Education is segregated into 5 categories of less than high school (1.6%), senior secondary (0.6%), higher secondary (9.6%), bachelor's degree (51.2%) and advanced degree (37%). The income was divided into 6 categories based on the tax slab of 2018-19 (Tax SLAB 2018-19, n.d.) with the majority of respondents falling into the category of income bracket 5-10 lakh(29.8%), up to 2 lakh (27%), 2.5-5 lakh (22.4%) and the rest belonged to above 50 lakh – 1 crore(2.4%)and finally above 1 crore (1.2%).

The choice of statistical method for data is dependent on the distribution of data collected. The data collected for the study does not follow the normality assumption and can be inferred from the p-value of the Shapiro-Wilk test and the large kurtosis values provided in table 5.1. After using the data transformation technique, the data still does not satisfy the normality test and hence PLS-SEM is preferred.

Table 5.1 Descriptive statistics

Constructs	Mean	Std. Deviation	Skewness	Kurtosis	P-value of Shapiro-Wilk
PE	6.151	1.269	-2.486	6.455	< .001
EE	6.279	1.267	-2.856	8.265	< .001
SI	5.712	1.405	-1.451	1.841	< .001
FC	6.014	1.236	-2.221	5.22	< .001
HM	5.702	1.533	-1.365	1.324	< .001
PV	5.869	1.363	-1.673	2.791	< .001
H	5.588	1.331	-1.245	1.313	< .001
BI	6.132	1.221	-2.208	5.407	< .001
TC	6.071	1.346	-2.029	3.969	< .001
TECC	6.088	1.205	-2.048	4.717	< .001
TTF	6.02	1.188	-2.042	4.813	< .001
PS	5.713	1.302	-1.368	1.879	< .001
GP	5.534	1.277	-1.148	1.039	< .001

5.2. PLS Algorithm

The study uses the partial least square (PLS) method to analyze the data collected and to evaluate the variance explained by the proposed model. PLS is one of the popular variants of path modeling which is also known as structural equation modeling. This method has its origin from the seminal work presented by Herman World about principal component analysis (Wold, 1966). The method is less reliant on distributions and large sample size (Reinartz et al., 2009; Ringle et al., n.d.), which is a better option compared to covariance SEM (CB-SEM) if the data collected doesn't follow normality. PLS is an ideal tool to develop theories or extend established theories as well as to make predictions (J. F. Hair et al., 2011).

PLS path modeling is a causal approach to explain the maximum variance in the endogenous constructs(J. F. Hair et al., 2011). Before evaluating the structural model, an assessment of the measurement model and structural model is carried out.

5.3. Measurement model

The measurement model helps us to measure the unobserved phenomenon (Latent Variable) through the observed indicators. These observed indicators can be related to their associated latent variables in three ways i.e. reflective, formative, and multiple effect indicators for multiple causes (Tenenhaus et al., 2005). In this study, all the constructs are reflectively measured, and each indicator variable is related to its latent variable by a regression equation. The following equation is a direct adoption from (Tenenhaus et al., 2005)

$$x_h = \pi_{ho} + \pi_h \xi + \varepsilon_h \qquad 5\text{-}1$$

Where,

x_h = observed indicator variable, ξ = Associated latent variable

Tenenhaus suggested performing Unidimesionality checks by conducting principal component analysis, Cronbach's alpha, and Dillon-Goldstein's ρ also known as composite reliability. These tests are to be carried out for each block, where every block has a few indicators associated with a single construct (Tenenhaus et al., 2005). In PLS-SEM a priori knowledge about the constructs is integrated into the algorithm. The first unidimensionality check is performed by conducting a principal component analysis of a block of indicators associated with a latent construct. The block is unidimensional if the first eigen value of the correlation matrix is greater than 1 and the second eigen value is smaller.

From the proposed model consisting of 13 latent constructs and 47 indicator variables, all the indicator variables loaded highly on a single factor as only one factor was extracted with eigen value > 1 during principal component analysis. Details of block level association of eigen values are mentioned in Table 5.2. The graphical representation of the eigen values associated with their respective latent construct is presented in figure 5.1 as a scree plot. The quantum of the first eigen value of each latent construct is greater than one and the subsequent eigen values are below the threshold level. This establishes the unidimensionality of the latent constructs proposed in the study.

Table 5.2 Block unidimensionality

Constructs	No. of components	1^{st} eigen value	2^{nd} eigen value
PE	4	3.17	0.34
EE	4	3.51	0.19
SI	3	2.58	0.23
FC	4	2.91	0.55
HM	2	1.78	0.22
PV	3	2.34	0.42
H	4	2.64	0.67
BI	3	2.26	0.43
TC	3	2.37	0.39
TECC	3	2.39	0.36
TTF	3	2.44	0.30
PS	4	3.02	0.47
GP	7	3.36	0.85

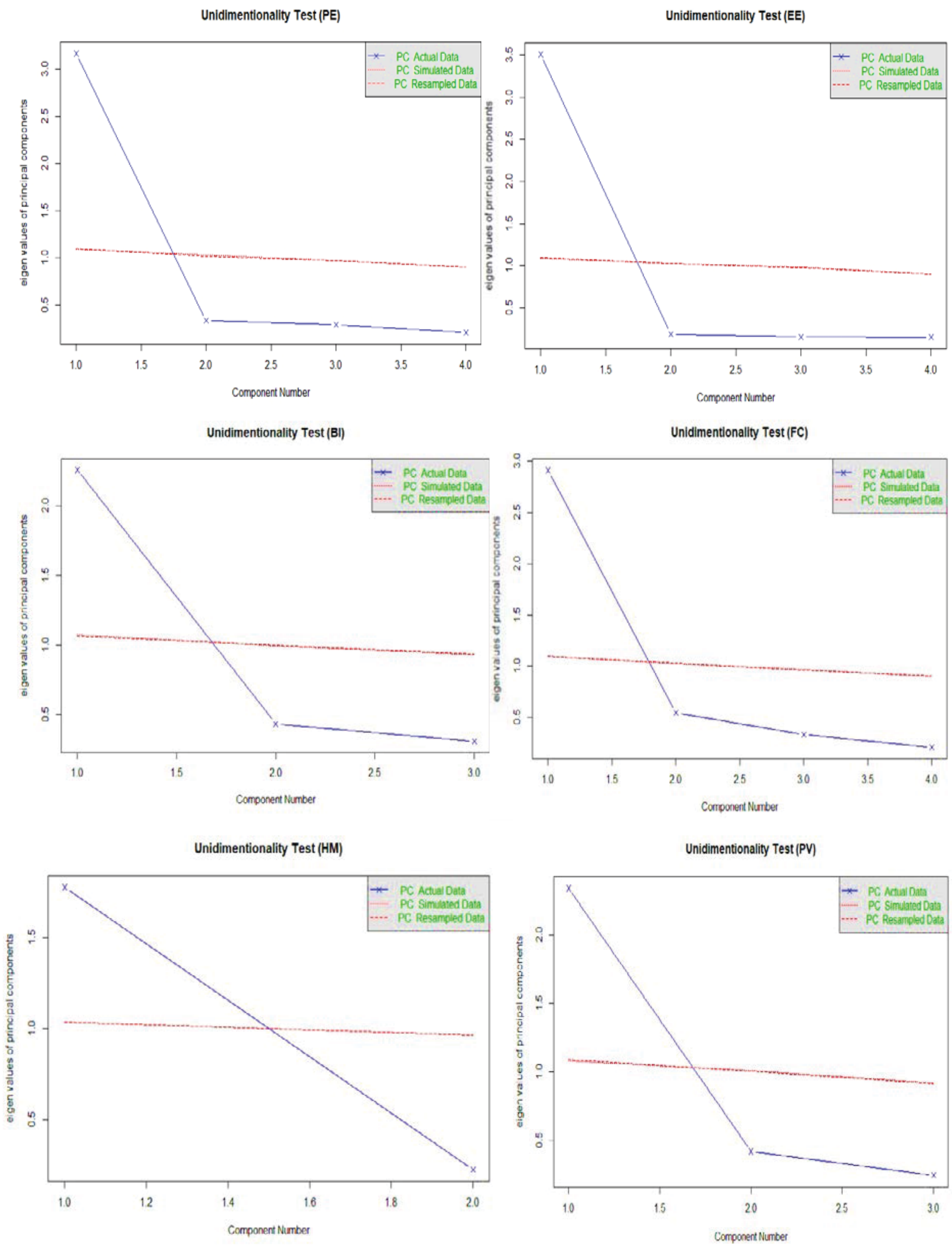

Figure 5.1 Scree Plot of eigen values associated with their latent constructs

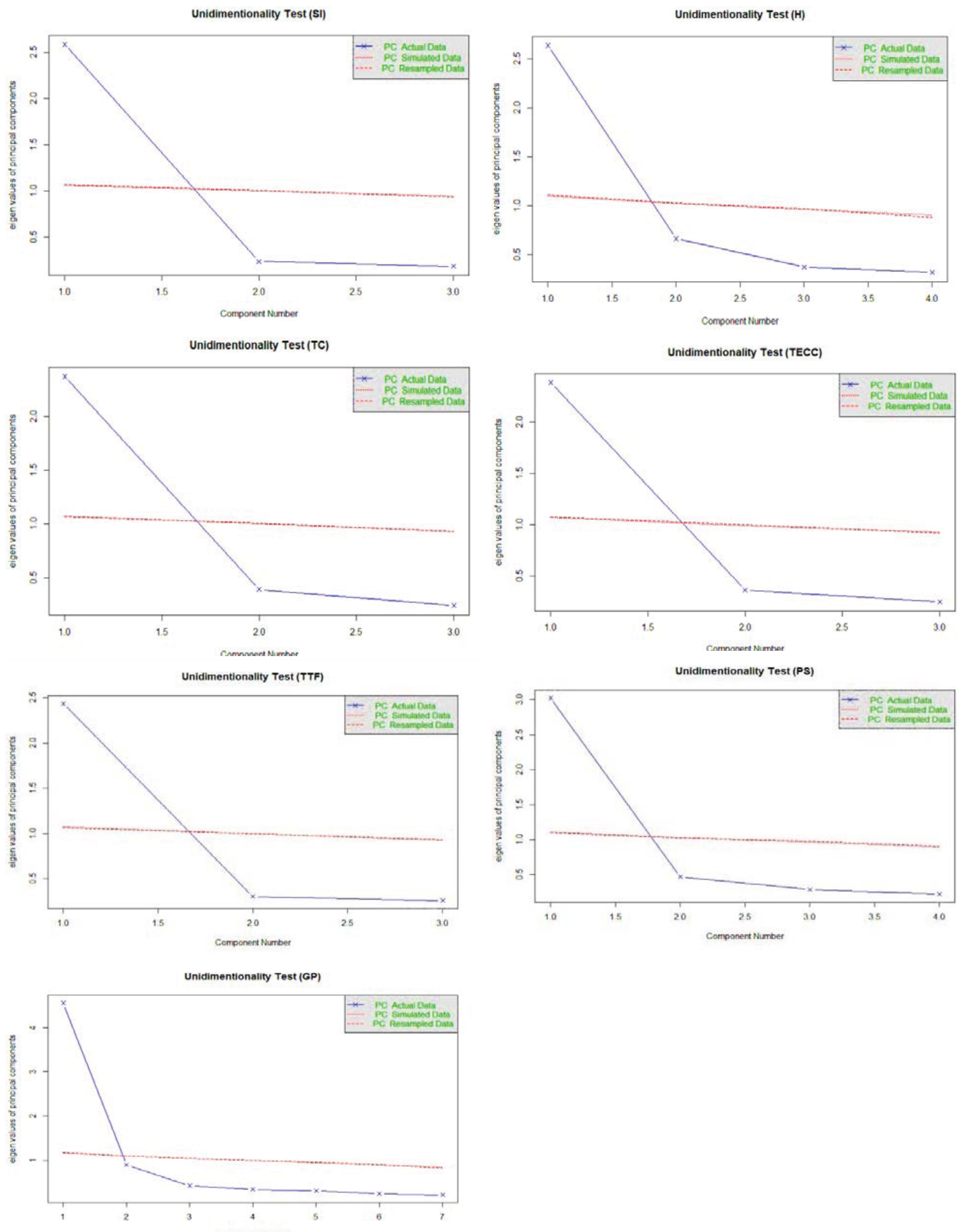

Figure 5.1 Contd... Scree Plot of eigen values associated with their latent constructs

Calculation of Cronbach's alpha (CA) and Dillion-Goldstein's ρ (composite reliability) are categorized as indicator reliability and constructs' internal consistency. Cronbach's alpha considers all the indicators equally reliable but composite reliability (CR) puts a priority on indicators during model estimation (J. F. Hair et al., 2011). From Table 5.3 it is evident that the scores are above of threshold limit of 0.7, hence establishing both composite and indicator reliability (Jörg Henseler et al., 2014).

Table 5.3 Indicator Reliability

	SI	FC	HM	PV	H	PS	TC	TECC	EE	TTF	PE	BI
CR	0.95	0.91	0.94	0.94	0.88	0.94	0.95	0.93	0.97	0.93	0.94	0.93
CA	0.92	0.87	0.87	0.91	0.83	0.92	0.91	0.88	0.95	0.88	0.91	0.88

The next step of measurement model checks is to establish the convergent validity. Convergent validity checks whether an indicator correlates positively with other indicators associated with the same latent variable. The metric used for measuring convergent validity is average variance extracted (AVE), which is the average of the sum of squared loadings. The values of all the AVE measures are above the threshold limit of 0.5 (J. F. Hair et al., 2011), Therefore convergent validity is established. Along with the AVE values it is also common practice to consider removing outer loadings with values less than 0.5 unless it is necessary to preserve the content validity. Outer loadings with values less than 0.4 should always be removed (Bagozzi et al., 1991). In table 5.4 the AVE values are represented on the diagonal of the matrix, and it can be observed that the square root of AVE of each latent construct is higher than the inter- construct correlation.

Table 5.4 Indicator Reliability and AVE

Outer Loadings	Estimate	Indicator reliability	AVE
Social Influence			
SI1	0.92	0.84	0.86
SI2	0.94	0.87	
SI3	0.93	0.87	
Facilitating Conditions FC1	0.88	0.78	0.73
FC2	0.91	0.83	
FC3	0.87	0.76	
FC4	0.73	0.54	
Hedonic Motivation			
HM1	0.93	0.86	0.89
HM2	0.95	0.91	
Price Value			
PV1	0.88	0.78	0.84
PV2	0.94	0.88	
PV3	0.93	0.87	
Habit			
H1	0.86	0.74	0.66
H2	0.78	0.61	
H3	0.81	0.66	
H4	0.79	0.62	
Perceived Security			
PS1	0.90	0.80	0.80
PS2	0.89	0.80	
PS3	0.90	0.82	
PS4	0.89	0.80	
Task Characteristics			
TC1	0.92	0.86	0.85
TC2	0.91	0.83	
TC3	0.94	0.87	
Technology Characteristics			
TECC1	0.89	0.79	0.81
TECC2	0.92	0.84	
TECC3	0.89	0.79	
Effort Expectancy			
EE1	0.94	0.89	0.88
EE2	0.94	0.88	
EE3	0.94	0.88	
EE4	0.93	0.87	
Task Technology Fit			
TTF1	0.91	0.82	0.81
TTF2	0.90	0.82	
TTF3	0.89	0.80	
Performance Expectancy PE1	0.89	0.79	0.79
PE2	0.88	0.77	
PE3	0.91	0.82	
PE4	0.88	0.78	

Behavioural Intention			
BI1	0.89	0.79	0.81
BI2	0.90	0.81	
BI3	0.91	0.82	

The final step for evaluating measurement model is to establish discriminant validity, which empirically measures how distinct a particular latent construct is from other latent constructs in the same model. Followings are the three approaches to measure discriminant validity:

- Cross-loading analysis,
- Fornell-Larcker criterion and
- Heterotrait-monotrait ratio (HTMT).

Cross loading analysis is an assessment of the indicators' outer loading with respect to all the latent constructs. The indicators are expected to have the highest correlation with their associated constructs over other constructs in the model. Cross loading analysis was performed using ADANCO 2.2.1 (Jörg; Henseler & Dijkstra, 2020).

Table 5.5 presents the cross-loading matrix of all the indicators with respect to the latent construct used in the study. The highest loading for an indicator is marked in bold and it is evident that the indicators have the highest loadings on their respective constructs rather than their cross-loadings hence it satisfies the cross-loading analysis.

Table 5.5 Cross Loading

Indicator	**SI**	**FC**	**HM**	**PV**	**H**	**TC**	**TECC**	**TTF**	**PS**	**BI**	**PE**	**EE**
PE1	0.67	0.72	0.61	0.66	0.58	0.57	0.61	0.61	0.56	0.66	**0.90**	0.77
PE2	0.73	0.65	0.65	0.67	0.64	0.64	0.65	0.63	0.63	0.66	**0.89**	0.73
PE3	0.68	0.81	0.64	0.69	0.60	0.62	0.68	0.64	0.58	0.71	**0.91**	0.87
PE4	0.72	0.69	0.66	0.69	0.61	0.61	0.63	0.63	0.62	0.66	**0.89**	0.74

EE1	0.64	0.81	0.63	0.67	0.56	0.56	0.63	0.63	0.54	0.62	0.82	**0.94**
EE2	0.69	0.78	0.64	0.67	0.58	0.55	0.62	0.61	0.56	0.62	0.82	**0.92**
EE3	0.63	0.81	0.62	0.65	0.55	0.54	0.65	0.62	0.54	0.63	0.81	**0.94**
EE4	0.60	0.78	0.61	0.66	0.53	0.54	0.61	0.63	0.54	0.58	0.76	**0.91**
SI1	**0.92**	0.60	0.64	0.64	0.64	0.62	0.61	0.58	0.60	0.64	0.72	0.65
SI2	**0.94**	0.61	0.65	0.62	0.64	0.59	0.58	0.57	0.59	0.63	0.72	0.63
SI3	**0.93**	0.64	0.66	0.63	0.64	0.62	0.65	0.63	0.62	0.66	0.73	0.64
FC1	0.58	**0.88**	0.56	0.65	0.53	0.50	0.61	0.61	0.52	0.59	0.71	0.76
FC2	0.59	**0.91**	0.57	0.63	0.49	0.52	0.62	0.59	0.51	0.57	0.76	0.84
FC3	0.59	**0.88**	0.64	0.61	0.56	0.51	0.60	0.59	0.55	0.63	0.71	0.71
FC4	0.47	**0.73**	0.50	0.52	0.38	0.34	0.45	0.40	0.39	0.40	0.52	0.57
HM1	0.61	0.58	**0.94**	0.61	0.62	0.55	0.54	0.60	0.54	0.58	0.62	0.60
HM2	0.70	0.67	**0.95**	0.73	0.70	0.65	0.68	0.69	0.66	0.68	0.72	0.67
PV1	0.57	0.61	0.60	**0.88**	0.60	0.53	0.59	0.58	0.61	0.57	0.61	0.60
PV2	0.65	0.67	0.67	**0.94**	0.67	0.63	0.70	0.67	0.70	0.73	0.73	0.67
PV3	0.63	0.67	0.68	**0.93**	0.66	0.61	0.68	0.65	0.66	0.68	0.71	0.68
H1	0.64	0.61	0.66	0.66	**0.87**	0.66	0.71	0.72	0.67	0.78	0.67	0.63
H2	0.53	0.35	0.55	0.53	**0.81**	0.57	0.55	0.52	0.58	0.60	0.46	0.36
H3	0.61	0.41	0.56	0.57	**0.85**	0.67	0.67	0.62	0.65	0.71	0.55	0.45
H4	0.52	0.54	0.57	0.58	**0.82**	0.62	0.64	0.68	0.65	0.73	0.57	0.53
BI1	0.61	0.64	0.62	0.69	0.75	0.74	0.77	0.75	0.70	**0.91**	0.72	0.66
BI2	0.65	0.56	0.62	0.66	0.80	0.75	0.74	0.71	0.71	**0.92**	0.67	0.57
BI3	0.64	0.60	0.61	0.66	0.78	0.74	0.76	0.73	0.74	**0.93**	0.67	0.59
TC1	0.61	0.50	0.60	0.60	0.72	**0.92**	0.70	0.66	0.66	0.76	0.61	0.52
TC2	0.58	0.52	0.57	0.58	0.68	**0.92**	0.73	0.69	0.68	0.73	0.61	0.54
TC3	0.63	0.53	0.59	0.62	0.70	**0.94**	0.74	0.72	0.67	0.76	0.66	0.57
TECC1	0.57	0.57	0.56	0.65	0.68	0.70	**0.89**	0.70	0.69	0.71	0.62	0.58
TECC2	0.59	0.64	0.58	0.65	0.71	0.71	**0.92**	0.76	0.71	0.76	0.66	0.63
TECC3	0.62	0.61	0.61	0.64	0.69	0.69	**0.89**	0.77	0.77	0.75	0.65	0.61
TTF1	0.59	0.57	0.65	0.62	0.71	0.68	0.77	**0.91**	0.72	0.71	0.60	0.60
TTF2	0.59	0.59	0.60	0.64	0.67	0.69	0.75	**0.91**	0.74	0.71	0.65	0.60
TTF3	0.56	0.62	0.60	0.62	0.70	0.66	0.73	**0.90**	0.71	0.73	0.63	0.61
PS1	0.57	0.52	0.56	0.64	0.67	0.65	0.74	0.71	**0.91**	0.69	0.60	0.53
PS2	0.58	0.52	0.58	0.66	0.68	0.62	0.70	0.72	**0.90**	0.68	0.57	0.53
PS3	0.58	0.51	0.59	0.63	0.69	0.65	0.73	0.73	**0.91**	0.70	0.60	0.52
PS4	0.62	0.57	0.59	0.67	0.72	0.70	0.75	0.75	**0.91**	0.74	0.63	0.56

The next approach is the Fornell-Larcker criterion (Fornell & Larcker, 1981) which compares the square root of AVE values against the correlation with other latent constructs. The logic behind this approach is the latent variable should explain more variance with its indicators than with other constructs. Table 5.6 is a correlation matrix between the constructs used in the study and their AVE values are presented on the diagonal of the matrix and are marked in bold. An evaluation of the matrix suggests the AVE values are higher than the correlation values with other latent constructs and hence, the constructs used in the do not suffer from discriminant validity problems.

Table 5.6 Fornell-Larker Matrix

	SI	**FC**	**HM**	**PV**	**H**	**PS**	**TC**	**TECC**	**EE**	**TTF**	**PE**	**BI**
SI	**0.86**											
FC	0.44	**0.73**										
HM	0.47	0.45	**0.89**									
PV	0.43	0.52	0.48	**0.84**								
H	0.43	0.36	0.45	0.46	**0.66**							
PS	0.38	0.34	0.36	0.49	0.56	**0.80**						
TC	0.39	0.31	0.34	0.39	0.53	0.47	**0.85**					
TECC	0.41	0.45	0.39	0.49	0.58	0.63	0.60	**0.81**				
EE	0.46	0.73	0.43	0.51	0.34	0.33	0.32	0.43	**0.88**			
TTF	0.38	0.41	0.43	0.46	0.58	0.62	0.52	0.67	0.41	**0.81**		
PE	0.57	0.67	0.48	0.56	0.40	0.39	0.40	0.48	0.76	0.44	**0.79**	
BI	0.41	0.47	0.40	0.51	0.66	0.56	0.61	0.69	0.43	0.63	0.50	**0.81**

The final approach for discriminant validity is the Assessment of HTMT ratios (Jörg Henseler et al., 2015). This method was introduced to overcome the shortcomings of the Fornell-Larcker criterion where the loadings are inflated if the number of indicators is small (Aguirre-Urreta et al., 2013). Henseler et al.'s (2015) method of HTMT ratios are based on the Multitrait-multimethod (Campbell & Fiske, 1959). There are two ways to assess discriminant validity using the HTMT matrix, the absolute criteria, and inference criteria. While the absolute criteria suggest that the HTMT ratios should not exceed 0.85 but absolute HTMT value of 0.90 is also accepted. HTMT inference is the most lenient criteria as it checks whether the 90% bootstrap confidence interval with a Bonferroni adjustment applied to the HTMT criterion includes the value 1. The 0.85 threshold has a better sensitivity of 99.9% compared to 99.45% for the 0.90 thresholds and 97.01% for the HTMT inference approach.

The matrix presented in Table 5.7 represents the HTMT criterion values in the lower triangle and the upper triangle contains the HTMT inference values. HTMT ratio between EE-FC, PE-FC, BI-H, TTF-TECC, BI-TECC, and PE-EE are marked in bold and are higher than the threshold limit of 0.90 and hence the test for discriminant validity is not satisfied through absolute criterion, and inference criterion should be assessed. Although the criterion check fails to establish the discriminant validity, the HTMT inference check supports the discriminant validity as none of the values in the upper triangle contain 1. The next step is to assess the structural model.

Table 5.7 HTMT Matrix

	SI	FC	HM	PV	H	PS	TC	TECC	EE	TTF	PE	BI
SI	1.00	0.80	0.82	0.78	0.81	0.74	0.74	0.77	0.78	0.75	0.86	0.78
FC	0.74	1.00	0.82	0.86	0.77	0.73	0.71	0.83	0.96	0.81	0.94	0.85
HM	0.76	0.77	1.00	0.82	0.84	0.74	0.71	0.78	0.79	0.81	0.82	0.77
PV	0.72	0.81	0.77	1.00	0.84	0.82	0.77	0.85	0.83	0.82	0.87	0.85
H	0.75	0.69	0.78	0.78	1.00	0.89	0.87	0.92	0.73	0.92	0.80	0.96
PS	0.67	0.65	0.67	0.77	0.85	1.00	0.81	0.91	0.69	0.91	0.76	0.88
TC	0.68	0.61	0.64	0.69	0.83	0.75	1.00	0.91	0.70	0.85	0.78	0.92
TECC	0.71	0.76	0.70	0.78	0.89	0.88	0.86	1.00	0.81	0.96	0.85	0.97
EE	0.73	**0.93**	0.72	0.76	0.64	0.61	0.60	0.72	1.00	0.78	0.96	0.80
TTF	0.68	0.72	0.74	0.76	0.88	0.87	0.80	**0.92**	0.70	1.00	0.81	0.93
PE	0.82	**0.91**	0.77	0.82	0.71	0.68	0.69	0.77	**0.93**	0.74	1.00	0.86
BI	0.71	0.77	0.71	0.79	**0.94**	0.83	0.87	**0.94**	0.72	0.90	0.78	1.00

5.4. The Structural model

Collinearity assessment is a crucial step before interpreting the output from the PLS algorithm. Multi collinearity is the existence of two or more exogenous variables which are highly related to each other. The presence of multicollinearity in the model can provide unreliable estimates for the path coefficients. Variance inflation factor (VIF) is a metric to measure the degree to which the variance is inflated due to multicollinearity. The acceptable limit of VIF is 5 (J. F.

Hair et al., 2011; Kline, 2015). If the VIF value is above 5 it can affect the measure of path coefficients, possible solutions could be merging the latent constructs or dropping the problematic latent constructs. From Table 5.8 it is evident that the proposed model does not suffer from multicollinearity issues as all the values are below the threshold limit of 5.

Table 5.8 Collinearity Values

	TC	TECC	EE	TTF	SI	FC	HM	PV	H	PS	PE
TTF	2.50	2.50	-	-	-	-	-	-	-	-	-
PE	-	-	1.70	1.70	-	-	-	-	-	-	-
BI	-	-	-	-	2.80	3.42	2.65	3.19	2.90	2.73	4.37

5.5. Necessary Condition Analysis

Necessary condition analysis (NCA) is bi-variate statistical method which presents the latent factors which are essential to achieve a desired level of outcome even if they might not be statistically significant in PLS-SEM (Dul, 2016). This method helps to complement PLS-SEM where the focus is on to establish sufficiency criteria.

There are two ways to assess the necessity criteria: first, the graphical method which is a scatter plot between the exogenous variable and endogenous variable as presented in figure 5.2. The celling lines: ceiling envelopment-free disposal hull (CE-FDH) and celling regression - free disposal hull (CR-FDH) are the two default lines that separate the space containing observations and space with no observations in the scatter plot. A larger no observation area makes that latent factor to be necessary even for achieving low levels of output, hence makes the latent factor more important. Second, the bottleneck table presents the necessity criteria to achieve desired output levels. Table 5.9 presents the bottleneck table where the latent factors are evaluated vis-à-vis the output (BI) mentioned in the first column. This table is the numerical representation of the scatter plot mentioned in figure 5.2.

Factor scores are used to run the analysis using NCA package in R (Dul, 2020b), this helps to act as a bridge between the theory and necessity condition in the context of PLS-SEM (Richter et al., 2020). It is evident from table 5.9 that HM, GP, EE, and PE are not necessary at any level of the output BI. The necessity effect size (d) and its significance are presented in table 5.10 where the values of effect size can range from 0 to 1. Values from 0 to 0.1 signifies small effect, 0.1 to 0.3 as medium effect , 0.3 to 0.5 as large effect and values above 0.5 represents very large effect (Dul, 2016, 2020a).

Table 5.9 Bottleneck table

BI	SI	FC	HM	PV	H	PS	GP	TC	TECC	EE	TTF	PE
0	NN	NN	NN	NN	NN	NN	NN	NN	11.5	NN	NN	NN
10	NN	NN	NN	NN	16.7	NN	NN	NN	11.5	NN	11.2	NN
20	NN	NN	NN	NN	21	16.7	NN	NN	21.8	NN	11.2	NN
30	NN	4.5	NN	NN	21	16.7	NN	NN	21.8	NN	16.7	NN
40	NN	4.5	NN	NN	22.3	16.7	NN	NN	21.8	NN	21.8	NN
50	NN	4.5	NN	NN	22.3	16.7	NN	NN	21.8	NN	21.8	NN
60	NN	4.5	NN	NN	22.3	16.7	NN	NN	21.8	NN	21.8	NN
70	NN	4.5	NN	NN	23.7	16.7	NN	NN	21.8	NN	21.8	NN
80	NN	4.5	NN	NN	26	16.7	NN	NN	28.2	NN	33.2	NN
90	10.8	4.5	NN	9.8	50.2	36.7	NN	33.3	56	NN	44.7	NN
100	10.8	4.5	NN	9.8	50.2	36.7	NN	33.3	56	NN	55.3	NN

Note: NN = Not necessary

Table 5.10 Effect size (d) for necessity w.r.t their respective celling lines

	SI	FC	HM	PV	H	PS	GP	TC	TECC	EE	TTF	PE
CE-FDH	0.018	0.032	0	0.016	0.255	0.172	0	0.052	0.256	0	0.237	0
Significant	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No
CR-FDH	0.009	0.016	0	0.011	0.235	0.119	0	0.038	0.246	0	0.222	0
Significant	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No

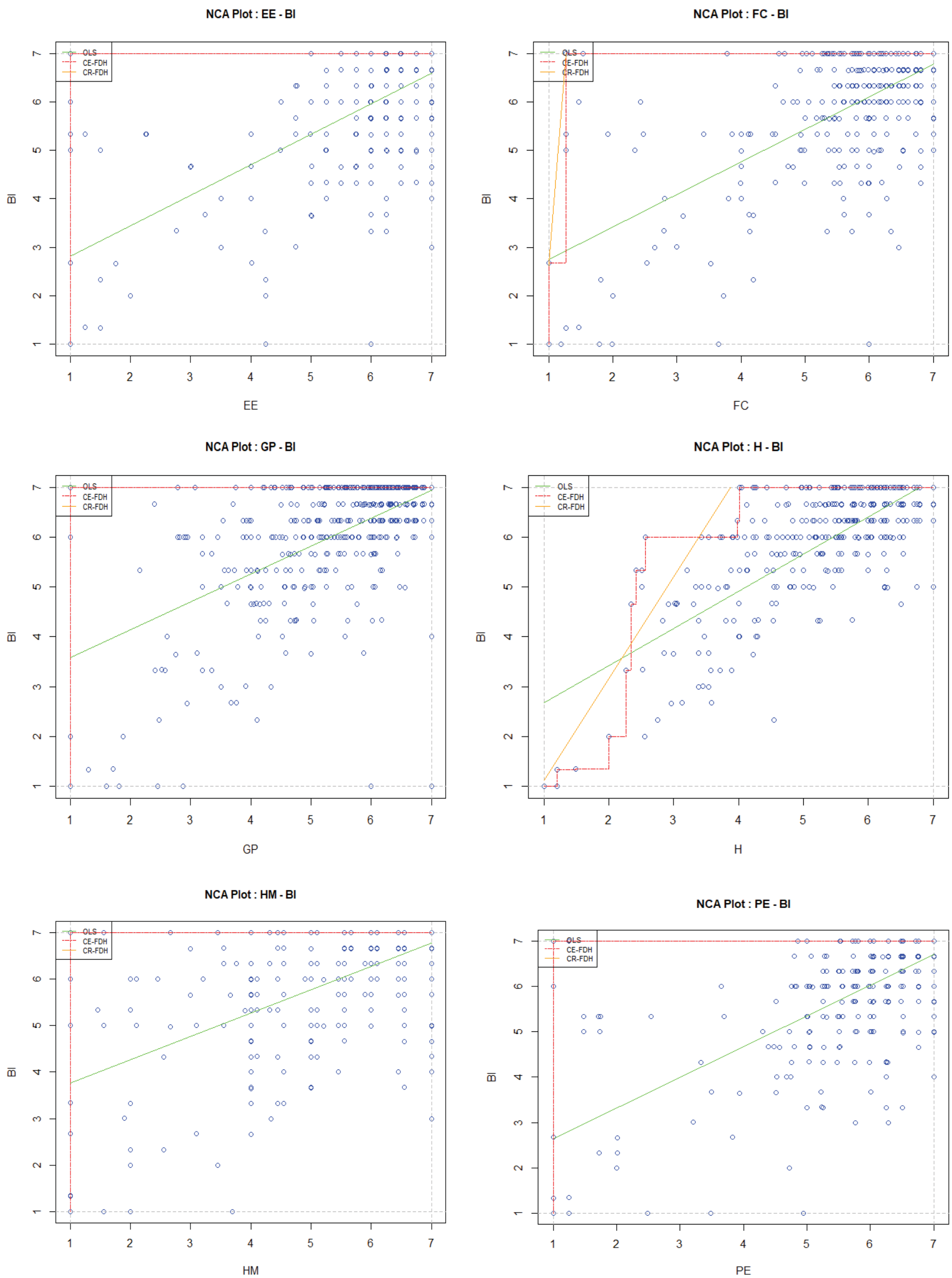

Figure 5.2 Scatter Plots

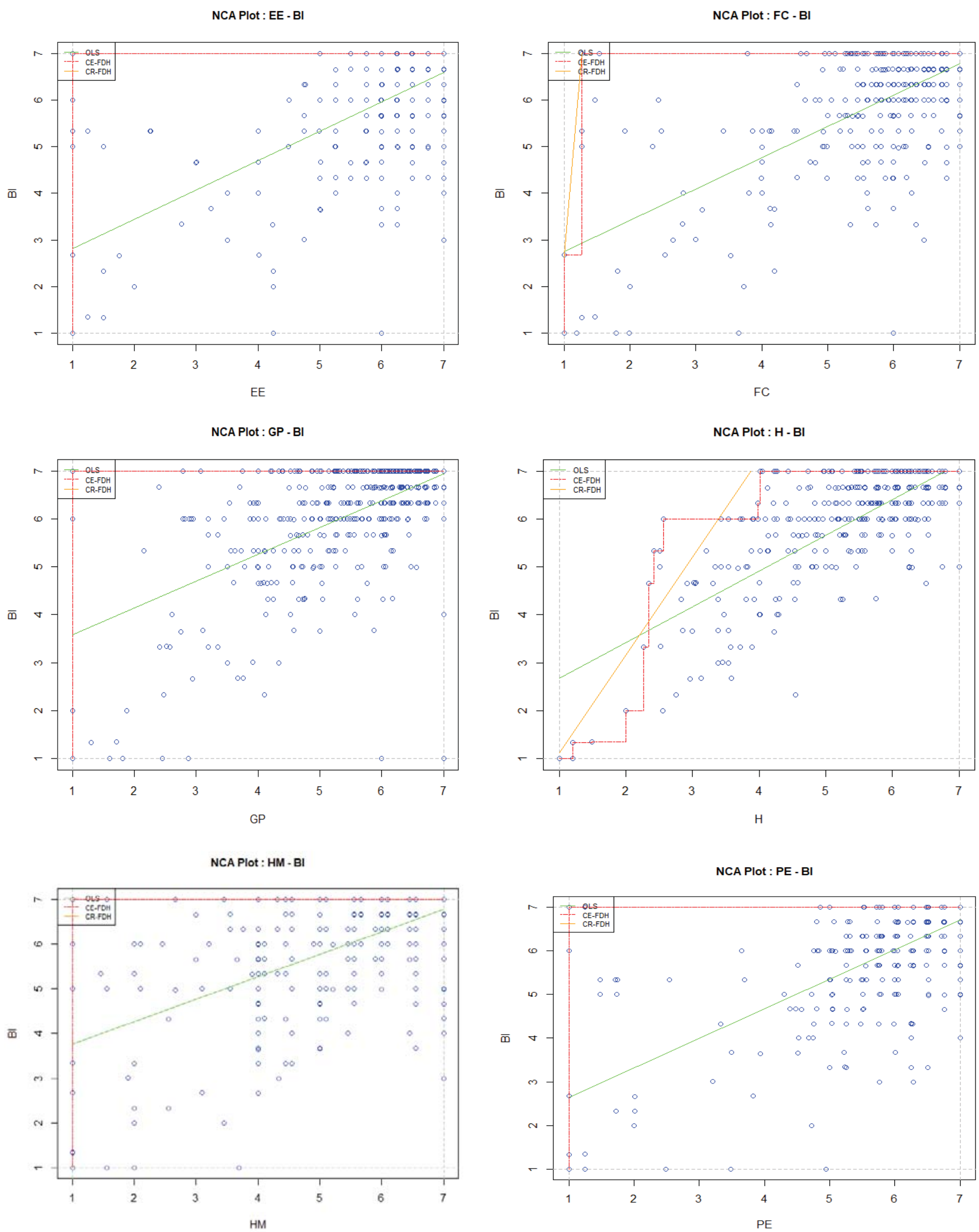

Figure 5.2 contd... Scatter Plots

5.6. Model Estimation and Evaluation

The objective of the PLS-SEM algorithm is to maximize the explained variance for the endogenous construct which is different from the CB-SEM, where the algorithm minimizes the difference between sample and model predicted covariance matrix. Hence model fit cannot be applied to PLS-SEM. The model evaluation is based on its predictive capabilities and the metrics employed to perform this procedure are path coefficients, R^2 of the endogenous construct, and Cohen's f^2 effect size for direct effects.

The path coefficients are standardized and can have values between -1 and +1. Values closer to + 1 signify a stronger relationship and the farther they are the strength of the relationship decreases. The statistical significance of the path coefficients is calculated from the standard error obtained by using a bootstrapping procedure. The bootstrap confidence interval also helps us to make inferences regarding the significance of path coefficients. If the confidence interval does not include zero, then we can assume the significance of the effect.

Among various bootstrapping approaches Bias-corrected and accelerated (BCa) confidence interval suggested by Bradley Efron is preferred (Efron, 1987; Gudergan et al., 2008; Sarstedt et al., 2011). The PLS-SEM analysis is implemented using the cSEM (Rademaker & Schuberth, 2020) package for the R programming language (R Core Team, 2013). The BCa approach can be implemented by conduction double bootstrap in cSEM package with two tail testing. 5000 samples were used in the process with no sign changes option and two tail options (J. Hair et al., 2017).

The path coefficient of the proposed model is presented in Table 5.11 for direct effects and table 5.12 for indirect effects, where all the coefficients are significant except social influence (BI ← SI), hedonic motivation (BI← HM), and price value (BI← PV) are not significant. The small path coefficient is due to the large sample size (N = 500) used in the study (J. Hair et al., 2017). The relevance of these relationships should be interpreted relative to each other, where the highest coefficient has the largest effect, and the rest are ranked based on their coefficients (Wixom & Watson, 2008). Cohen categorized the effect size of 0.02 as small, 0.15 as a medium, and 0.35 as large. From table 5.11 we can identify only habit has a medium effect ($f^2 = 0.30$) on behavioural intention while the rest of the significant predictors (FC, PS, PE, and TTF) have a small effect (Cohen, 1988).

Table 5.11 Direct Effects

Hypothesis	**Path**	**Estimate**	**p-value**	**CI_percentile 95%**	**Cohen f^2**	**Inference**
H10(d)	TECC → EE	0.66	0.00**	[0.5521; 0.7539]	0.76	Do not Reject
H9(a)	TC → TTF	0.23	0.00**	[0.0992; 0.3596]	0.07	Do not Reject
H10(a)	TECC → TTF	0.64	0.00**	[0.5071; 0.7673]	0.52	Do not Reject
H1(a)	EE → PE	0.76	0.00**	[0.6642; 0.8260]	-	Do not Reject
H11(a)	TTF → PE	0.17	0.00**	[0.1025; 0.2692]	0.08	Do not Reject
H3	SI → BI	-0.02	0.65	[-0.1180; 0.0766]	0.00	Reject
H4	FC → BI	0.16	0.00**	[0.0458; 0.2442]	0.03	Do not Reject
H5	HM → BI	-0.06	0.24	[-0.1693; 0.0427]	0.01	Reject
H8	PV → BI	0.08	0.09	[-0.0072; 0.1548]	0.01	Reject
H6	H → BI	0.47	0.00**	[0.3625; 0.5549]	0.30	Do not Reject
H7	PS → BI	0.21	0.00**	[0.1209; 0.3154]	0.07	Do not Reject
H2	PE → BI	0.15	0.03	[0.0256; 0.2946]	0.02	Do not Reject

Note: *P<0.1, **P<0.05, *** p<0.01

Table 5.12 Indirect Effects

Hypothesis	**Path**	**Estimate**	**p-value**	**CI_percentile 95%**	**Inference**
H11(a)	TC → PE	0.47	0.00**	[0.3759; 0.5419]	Do not Reject
H10(b)	TECC → PE	0.11	0.00**	[0.0672; 0.1892]	Do not Reject

H9(c)	TC → BI	0.07	0.03**	[0.0122; 0.1397]	Do not Reject
H10(c)	TECC → BI	0.02	0.12	[0.0021; 0.0440]	Reject
H1(b)	EE → BI	0.12	0.02**	[0.0203; 0.2170]	Do not Reject
H11(b)	TTF → BI	0.03	0.09**	[0.0037; 0.0611]	Do not Reject

Note: *P<0.1, **P<0.05, *** p<0.01

While making inferences about the proposed hypothesis the total effect is calculated, which is the sum of direct and indirect effects. Table 5.13 provides a summary of all the proposed hypothesis and their inference.

The model's predictive power is calculated using the coefficient of determination (R^2). The R^2 value of the model is 0.77, which higher level of predictive accuracy (J. F. Hair et al., 2011; Jörg Henseler et al., 2009). This value represents the combined influence of all the exogenous constructs on the endogenous latent variable.

Table 5.13 Total Effects

Hypothesis	**Total effect**	**Estimate**	**p-value**	**CI_percentile 95%**	**Inference**
H10(d)	TECC → EE	0.66	0.00**	[0.5521; 0.7539]	Do not Reject
H9(a)	TC → TTF	0.23	0.00**	[0.0992; 0.3596]	Do not Reject
H10(a)	TECC→TTF	0.64	0.00**	[0.5071; 0.7673]	Do not Reject
H9(b)	TC → PE	0.47	0.00**	[0.3759; 0.5419]	Do not Reject
H10(b)	TECC → PE	0.11	0.00**	[0.0672; 0.1892]	Do not Reject
H1(a)	EE → PE	0.76	0.00**	[0.6642; 0.8260]	Do not Reject
H11(a)	TTF → PE	0.17	0.00**	[0.1025; 0.2692]	Do not Reject
H3	SI → BI	-0.02	0.65	[-0.1180; 0.0766]	Reject
H4	FC → BI	0.16	0.00**	[0.0458; 0.2442]	Do not Reject
H5	HM → BI	-0.06	0.24	[-0.1693; 0.0427]	Reject
H8	PV → BI	0.08	0.09	[-0.0072; 0.1548]	Reject
H6	H → BI	0.47	0.00**	[0.3625; 0.5549]	Do not Reject
H7	PS → BI	0.21	0.00**	[0.1209; 0.3154]	Do not Reject
H9(c)	TC → BI	0.07	0.03**	[0.0122; 0.1397]	Do not Reject
H10(c)	TECC → BI	0.02	0.12	[0.0021; 0.0440]	Reject
H1(b)	EE → BI	0.12	0.02**	[0.0203; 0.2170]	Do not Reject
H11(b)	TTF → BI	0.03	0.09	[0.0037; 0.0611]	Reject
H2	PE → BI	0.15	0.03**	[0.0256; 0.2946]	Do not Reject

5.7. Multi-Group Analysis

The multi-group analysis is another form of moderator analysis, the moderator variables in this situation are categorical in nature and are usually known to the researcher apriori (Vinzi et al., 2006). The possible moderator variables are Age, Gender, Education, and Income which can segment the population and may have distinct characteristics.

Multigroup analysis mainly checks for the various parameter's differences of path, loadings, and intercepts. The statistical significance of these differences can be analyzed using t-test and ANOVA. The distributional assumption of these tests makes it necessary for the dataset to be normally distributed. The CB-SEM-based methods have a precondition before conducting a multigroup analysis. These preliminary checks are referred to as the measurement invariance tests. (Keil et al., 2000) proposed a test based on the bootstrapping method but the statistical significance is calculated using t-statistics. These parametric methods are not applicable for data that is non-normal, and the latent constructs are reflective in nature. Nonparametric methods Measurement invariance of composite models (MICOM) requires the latent variables to be formative in nature(Jörg Henseler et al., 2016). The data collected for the study is non-normal and all the latent variables are reflectively measured hence a method that is not dependent on any distribution assumption and can be applied to reflective construct is preferred.

Chin and Dibbern proposed another test for multigroup analysis which was based on premutation (Chin and Dibbern 2010, p. 171). The permutation procedure was proposed by (Edgington, 2007). Permutation tests differ from randomization as it is not dependent on random assignment of cases and are dependent on only one assumption of independent observations. The significance is measured by the distribution of test statistics generated by the permutation of data. Two tests, (Chin and Dibbern 2010) and (Nitzl, 2012) are performed for the multigroup analysis in this study as both of these tests are based on permutation.

From table 5.14 and 5.15 presents the results of the Chin and Dibbern test and Nitzl test, respectively. It can be inferred that only two path coefficients are significant, hence the effect of effort expectancy on performance expectancy and task technology fit on performance expectancy is different due to gender differences in perception.

Table 5.14 Chin & Dibbern test

Hypothesis	Parameter	Test statistic	p-value	Inference
H 12(a)	TC → TTF	-0.07	0.66	Not significant
H 12(b)	TECC → TTF	0.05	0.68	Not significant
H 12(d)	EE → PE	0.27	0.02	Significant
H 12(c)	TTF → PE	-0.23	0.04	Significant
H 12(f)	SI → BI	0.04	0.71	Not significant
H 12(g)	FC → BI	-0.03	0.78	Not significant
H 12(h)	HM → BI	-0.11	0.33	Not significant
H 12(i)	PV → BI	-0.06	0.59	Not significant
H 12(j)	H → BI	0.01	0.94	Not significant
H 12(k)	PS → BI	0.16	0.10	Not significant
H 12(e)	PE → BI	-0.05	0.75	Not significant

Table 5.15 Nitzl test

Hypothesis	Parameter	Test statistic	p-value	Inference
H 12(a)	TC → TTF	-0.55	0.58	Not significant
H 12(b)	TECC → TTF	0.43	0.67	Not significant
H 12(d)	EE → PE	2.41	0.02	Significant
H 12(c)	TTF → PE	-2.11	0.04	Significant
H 12(f)	SI → BI	0.36	0.72	Not significant
H 12(g)	FC → BI	-0.29	0.77	Not significant
H 12(h)	HM → BI	-0.91	0.36	Not significant
H 12(i)	PV → BI	-0.57	0.57	Not significant
H 12(j)	H → BI	0.08	0.93	Not significant
H 12(k)	PS → BI	1.67	0.10	Not significant
H 12(e)	PE → BI	-0.32	0.75	Not significant

5.8. Moderator Analysis

A situation where the relationship between an endogenous construct and exogenous construct is dependent on the values of a third variable that is not directly dependent on the exogenous construct is called a moderating variable. A moderating variable has the potential to change the strength or/and direction of the relationship between the exogenous and endogenous variables. A moderator effect is studied by introducing an interaction term of the moderator variable and the exogenous construct. In this study, Government policy is taken as a moderator which is a continuous variable.

There are three major approaches to the inclusion of an interaction term i.e. product indicator approach (W. W. Chin et al., 2003), orthogonalizing approach (Little et al., 2006), and the two-stage approach (W. W. Chin et al., 2003; Fassott & Henseler, 2010).

The product indicator approach creates the interaction term by multiplying the indicators of the exogenous construct and the indicators of the moderator variable. The resulting product indicator terms serve as the indicators for the interaction term. But this process introduces collinearity which will inflate the standard error. A possible solution could be the standardization of indicators of the interaction term to minimize the effect. Still, standardization leads to the reduction of collinearity but does not eliminate it.

Building on the development of the product indicator approach Todd et.al (2006) proposed a new method (orthogonalizing approach) by using the indicators generated by the product indicator approach and regressing them onto the indicators of the exogenous construct and the moderator variable. This regression analysis will generate residuals and when these residuals are standardized, the new indicators will be orthogonal to the exogenous construct as well as the moderator variable. But orthogonalizing and product indicator approaches are applicable to reflective measures only.

A third alternative proposed by chin et.al (2003) uses a two-stage approach for moderator analysis. In the first stage, the latent variable scores are calculated without the interaction term, these scores are then multiplied to create the interaction effect. This method does not suffer from the limitation of the product indicator approach and orthogonalizing approach and can be applied to both reflective and formative constructs(Fassott & Henseler, 2010; Rigdon et al., 2010). The study uses a two-stage approach to conduct moderator analysis.

Before evaluating the model parameters all the tests related to the measurement model and structural model should be conducted. The Analysis will include a new moderator variable, government policy. The questions on government policy are measured on a scale of 1 to 7 with 1 representing strongly disagree and 7 representing strongly agree with the statement provided for evaluation.

The scales used in the study are adapted from previous studies on technology adoption and the detailed list of questions used for measuring government policy are mentioned in Appendix I on the questionnaire. All the questions are used in the study with context-based modification to preserve the content validity. The criterion reliability is satisfied as all the values mentioned in table 5.16 for composite reliability and Cronbach’s alpha are above the threshold limit of 0.7.

Table 5.16 Reliability_Moderator

	SI	FC	HM	PV	H	PS	GP	TC	TECC	EE	TTF	PE	BI
CR	0.95	0.91	0.94	0.94	0.88	0.94	0.94	0.95	0.93	0.97	0.93	0.94	0.93
CA	0.92	0.87	0.87	0.91	0.83	0.92	0.93	0.91	0.88	0.95	0.88	0.91	0.88

Convergent validity checks for the variance explained by the latent construct on the indicator variables. The AVE values should be more than 0.5 to show convergent validity. The outer loadings are presented in Table 5.17 are high on their respective constructs and the AVE values are higher than 0.5, the moderator model does not suffer from convergent validity issues.

Table 5.17 Convergent Vaidity_Moderator

Construct	Outer Loadings	Estimate	Indicator reliability	AVE
Social Influence	SI1	0.92	0.84	
	SI2	0.94	0.87	0.86
	SI3	0.93	0.87	
Facilitating Condition	FC1	0.88	0.78	
	FC2	0.91	0.83	0.73
	FC3	0.87	0.76	
	FC4	0.73	0.54	
Hedonic Motivation	HM1	0.93	0.86	0.89
	HM2	0.95	0.91	
Price Value	PV1	0.88	0.78	
	PV2	0.94	0.88	0.84
	PV3	0.93	0.87	
Habit	H1	0.86	0.74	
	H2	0.78	0.61	0.66
	H3	0.81	0.66	
	H4	0.79	0.62	
Perceived Security	PS1	0.90	0.80	
	PS2	0.89	0.80	0.80
	PS3	0.90	0.82	
	PS4	0.89	0.80	
Government Policy	GP1	0.84	0.71	
	GP2	0.82	0.67	
	GP3	0.85	0.71	
	GP4	0.82	0.67	0.71
	GP5	0.87	0.75	
	GP6	0.87	0.75	
	GP7	0.84	0.70	
Task Characteristics	TC1	0.92	0.86	
	TC2	0.91	0.83	0.85
	TC3	0.94	0.87	
Technology Characteristics	TECC1	0.89	0.79	
	TECC2	0.92	0.84	0.81
	TECC3	0.89	0.79	
Effort	EE1	0.94	0.89	0.88
	EE2	0.94	0.88	

Expectancy	EE3	0.94	0.88	
	EE4	0.93	0.87	
Task	TTF1	0.91	0.82	
Technology	TTF2	0.90	0.82	0.81
Fit	TTF3	0.89	0.80	
	PE1	0.89	0.79	
Performance	PE2	0.88	0.77	0.79
Expectancy	PE3	0.91	0.82	
	PE4	0.88	0.78	
Behavioural	BI1	0.89	0.79	
Intention	BI2	0.90	0.81	0.81
	BI3	0.91	0.82	

Discriminant validity measures how distinct the latent constructs are from each other. There are two ways of establishing discriminant validity through the examination of Fornell-Larcker and the HTMT matrix. Fornell-Larcker matrix is presented in Table 5.18, where the diagonal elements represent the square root AVE values and are higher than the other construct values beneath them.

Table 5.18 Fornell-Larcker Matrix_Moderator

	SI	FC	HM	PV	H	PS	GP	TC	TECC	EE	TTF	PE	BI
SI	0.86												
FC	0.44	0.73											
HM	0.47	0.45	0.89										
PV	0.43	0.52	0.48	0.84									
H	0.43	0.36	0.45	0.46	0.66								
PS	0.38	0.34	0.36	0.49	0.56	0.80							
GP	0.36	0.20	0.31	0.27	0.43	0.42	0.71						
TC	0.39	0.31	0.34	0.39	0.53	0.47	0.38	0.85					
TECC	0.41	0.45	0.39	0.49	0.58	0.63	0.38	0.60	0.81				
EE	0.46	0.73	0.43	0.51	0.34	0.33	0.22	0.32	0.43	0.88			
TTF	0.38	0.41	0.43	0.46	0.58	0.62	0.38	0.52	0.67	0.41	0.81		
PE	0.57	0.67	0.48	0.56	0.40	0.39	0.25	0.40	0.48	0.76	0.44	0.79	
BI	0.41	0.47	0.40	0.51	0.66	0.56	0.34	0.61	0.69	0.43	0.63	0.50	0.81

The next step is to evaluate the HTMT matrix for possible issues. The lower triangle of table 5.19 represents the criterion value of HTMT and the upper triangle represents the inference values. There are few values in the lower triangle which are higher than the threshold limit of 0.9 and it fails to pass the discriminant validity check, but inference criteria are satisfied as the upper triangle of table 5.19 does not contain 1.

Table 5.19 HTMT Matrix_Moderator

	SI	FC	HM	PV	H	PS	GP	TC	TECC	EE	TTF	PE	BI
SI	1.00	0.79	0.81	0.78	0.81	0.74	0.72	0.75	0.78	0.78	0.75	0.87	0.77
FC	0.74	1.00	0.82	0.87	0.78	0.72	0.59	0.71	0.83	0.96	0.80	0.94	0.85
HM	0.76	0.77	1.00	0.83	0.85	0.74	0.68	0.72	0.78	0.78	0.80	0.82	0.78
PV	0.72	0.81	0.77	1.00	0.84	0.82	0.65	0.76	0.84	0.84	0.81	0.87	0.85
H	0.75	0.69	0.78	0.78	1.00	0.89	0.82	0.87	0.92	0.73	0.92	0.79	0.97
PS	0.67	0.65	0.67	0.77	0.85	1.00	0.77	0.81	0.91	0.69	0.91	0.76	0.87
GP	0.65	0.49	0.61	0.56	0.74	0.70	1.00	0.75	0.76	0.60	0.76	0.63	0.73
TC	0.68	0.61	0.64	0.69	0.83	0.75	0.67	1.00	0.91	0.70	0.86	0.77	0.91
TECC	0.71	0.76	0.70	0.78	0.89	0.88	0.68	0.86	1.00	0.80	0.96	0.85	0.97
EE	0.73	0.93	0.72	0.76	0.64	0.61	0.50	0.60	0.72	1.00	0.78	0.96	0.80
TTF	0.68	0.72	0.74	0.76	0.88	0.87	0.68	0.80	0.92	0.70	1.00	0.82	0.93
PE	0.82	0.91	0.77	0.82	0.71	0.68	0.54	0.69	0.77	0.93	0.74	1.00	0.86
BI	0.71	0.77	0.71	0.79	0.94	0.83	0.64	0.87	0.94	0.72	0.90	0.78	1.00

After all discriminant validity checks are satisfactory the next step is to evaluate the structural model for collinearity issues. Table 5.20 presents the VIF values. All the values are below the threshold limit of 5, it is safe to assume that the model does not suffer from collinearity issues.

Table 5.20 VIF_Moderator

	TC	TECC	EE	TTF	SI	FC	HM	PV	H	PS	GP	PE
TTF	2.50	2.50	-	-	-	-	-	-	-	-	-	-
PE	-	-	1.70	1.70	-	-	-	-	-	-	-	-
BI	-	-	-	-	2.95	3.43	2.68	3.20	3.07	2.94	2.11	4.37

Figure 5.3 demonstrates the PLS-SEM results. The model evaluation is based on its predictive capabilities and the metrics employed to perform this procedure are path coefficients, R2 of the overall model is 0.75 without and 0.78 with the moderator (Government Policy). The model

has a higher explanatory power over other models explaining the adoption of mobile payments. The statistical significance of the path coefficients is calculated from the standard error obtained by using a bootstrapping procedure. The bootstrap confidence interval also helps us to make inferences regarding the significance of path coefficients. If the confidence interval does not include zero, then we can assume the significance of the effect. Among various bootstrapping approaches Bias-corrected and accelerated (BCa) confidence interval suggested by Bradley Efron is preferred (Efron, 1987; Gudergan et al., 2008; Sarstedt et al., 2011). The two-stage approach (W. W. Chin et al., 2003; Fassott & Henseler, 2010) was preferred for moderator analysis as it has a significant benefit over the product indicator approach (W. W. Chin et al., 2003), orthogonalizing approach (Little et al., 2006).

The results of moderator analysis are presented in table 5.21 where along with the hypothesis proposed for moderator analysis. In a previous analysis of the baseline model (refer to section 5.6) Hedonic motivation, social influence, price value, and task technology fit didn’t have any significant effect on behavioural intention but with the inclusion of government policy as a moderating variable we the interaction effect between task technology fit and government policy are having a significant effect and we can infer that while taking a decision on adoption for mobile payment systems compliance with government policy is also a contributing factor. The analysis also establishes the direct effect of government policy on behavioural intention is also significant.

Stone-Geisser’s Q^2 value is 0.75 for the behavioural intention which suggests a good out-of-sample prediction power.

Table 5.21 Moderating effect of government policy

Hypothesis	Total effect	Estimate	p-value	CI_percentile 95%	Inference
H13 (a)	GP → BI	0.300	0.02**	[0.1177; 0.6677]	Significant
H13 (c)	SIxGP → BI	-0.360	0.18	[-0.8644; 0.0835]	--
H13 (b)	TTFxGP → BI	0.480	0.00**	[0.3237; 0.7785]	Significant
H13 (d)	PVxGP → BI	0.144	0.69	[-0.4609; 0.9223]	--

Note: *P<0.1, **P<0.05, *** p<0.01

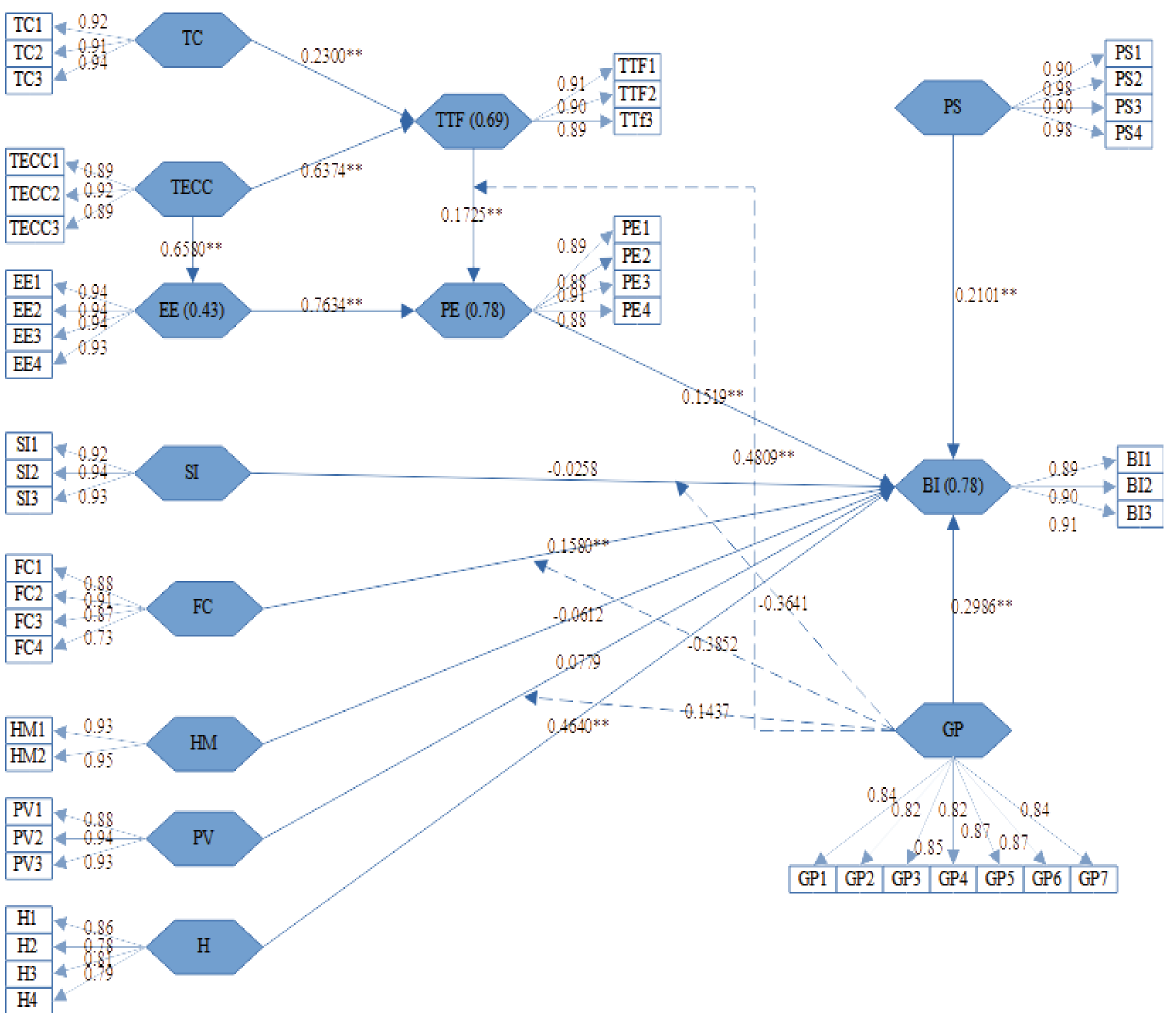

Figure 5.3 PLS- SEM Result

Note: *P<0.1, **P<0.05, *** p<0.01

5.9. Importance Performance Matrix Analysis (IPMA)

Importance performance analysis starts by identification of target variable on which the final effect is calculated. The target endogenous construct is usually the outcome variable or a crucial construct whose performance is related to the endogenous construct.

The following steps are performed for IPMA:

- A target construct of value is identified.
- PLS-SEM algorithm is used to maximize the R^2 value of the endogenous construct.
- The average construct scores are calculated.
- If the exogenous constructs are measured on different scales, then they are rescaled to a new scale of 0 to 100 for comparison.
- The values are then plotted to make inferences.

Importance performance map analysis can be represented as a scatterplot of the average value of construct scores and the coefficients of the total effect of the construct. In this study, the total effects are contrasted against the target endogenous construct of behavioural intention. Figure 5.4 is the graphical representation of IPMA. This method can be used as a tool to help identify the key areas of improvement.

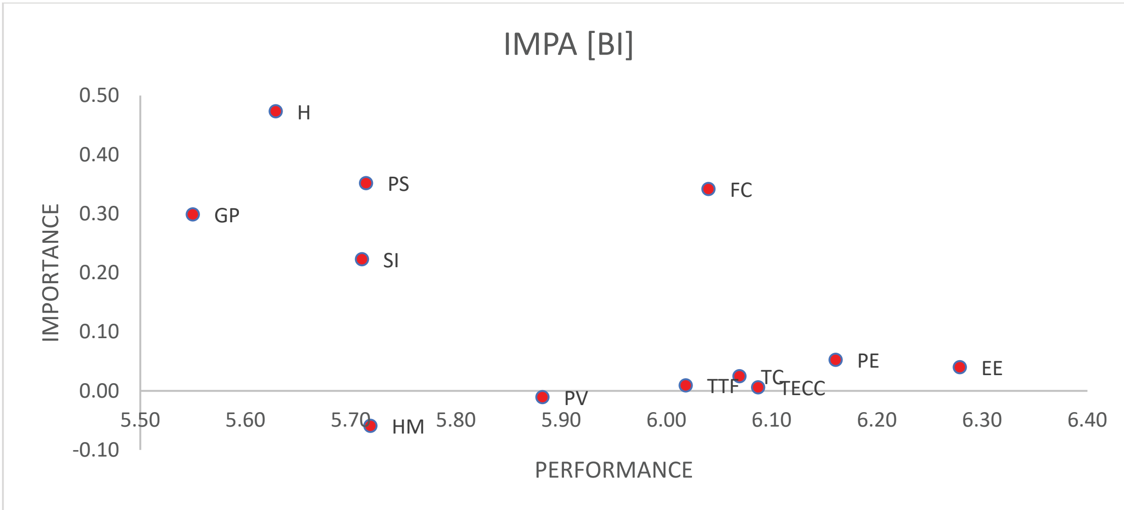

Figure 5.4 Importance performance map analysis

After the PLS-SEM analysis, we have found effort expectancy, performance expectancy, facilitating conditions, habit, task characteristics, perceived security, and government policy were found to have an overall significant effect on the intention to use mobile payments. The interaction effect of government policy and task technology fit is also deemed significant. Necessary conditions analysis is also conducted to complement the findings of PLS-Sem. Further analysis on importance-performance map analysis suggests there is a lot of room for improvement for habit, perceived security, and social influence. Multigroup analysis is also conducted to measure how gender plays a role in the intention to adopt mobile payments. The next chapter explains with respect to theories and other empirical evidence found in the literature.