CHAPTER 4

RESULTS AND ANALYSIS

4.1 Introduction

Chapter Four presents the data analysis based on the research objectives and hypotheses. The primary goal of the chapter is to present the results, which include descriptive statistics of the data and reliability and validity of the instrument, as well as outcomes of the hypotheses testing. This chapter shows the study results based on the data collected from customers of Jordanian commercial banks in north, central, and south Amman.

Chapter Four contains four sections. First, it presents the response rate, non-response bias, and common method bias tests. Second, it describes the initial data examination, screening, and preparation. The respondents' demographic characteristics are also detailed. Third, it shows the validity and reliability of the instrument. Finally, it describes the findings of the hypotheses testing, coefficients of determination, predictive relevance, and effect sizes.

4.2 Response Rate

The convenience sampling method was used to select the sample of this research. To distribute the questionnaires, the researcher personally visited 13 commercial banks in Amman and distributed 384 questionnaires to their customers. The surveys were personally administered and each questionnaire was attached with a pen as a gift. The researcher also assisted the respondents to expedite the answering process. The respondents were also reminded of the questionnaires through personal visits, phone calls, and SMS to increase the response rate (Sekaran & Bougie, 2010a). These efforts returned 378 questionnaires, indicating a response rate of 98.44 percent. However, six questionnaires were incorrectly filled, leaving only 372 questionnaires that were fit for analysis, indicating a valid response rate of 96.88 percent (Baruch & Holtom, 2008). The response rate is similar to previous research (Onyango, 2016; Talib et al., 2013; Wanyoike, 2016), hence it is considered satisfactory. The detailed response rate is shown in Table 4.1.

Table 4.1: Response Rate of the Questionnaires

Response	North of Amman	Central Amman	South of Amman	Freq/Rate
No. of distributed questionnaires	140	125	119	384
Returned questionnaires	138	122	118	378
Returned and usable questionnaires	135	121	116	372
Returned and excluded questionnaires	3	1	2	6
Questionnaires not returned	2	3	1	6
Response rate %	98.57	97.60	99.16	98.44
Usable response rate %	96.43	96.80	97.48	96.88

4.3 Sample Characteristics

The respondents were asked to answer several questions related to their profiles, such as gender, age, education level, and experience. The following are the demographic profile of the sample.

Firstly, the respondents were asked to indicate their gender. The descriptive analysis revealed that 51.1 percent of users were female, while 48.9 percent were male. This indicates that more than half of the users of online banking in Jordan are female. The respondents were also asked to indicate their age category. The largest percentage of users was 18-24 (48.9%), followed by between 25-31 (23.9%), between 32-38 (11.6%), between 39-45 (7.8%), between 46-52 (4.6%), and finally more than 52 (2.7%).

The education level of the respondents was also inquired. It was categorised into five levels: 1) high school or lower; 2) bachelor’s degree, 3) diploma; 4) master's degree; and 5) PhD. The respondents were asked to indicate their level of academic qualification. Most of the sample (69.9%) had a bachelor’s degree, followed by a master’s degree (14.8%), diploma (7%), PhD (5.4%), and high school or lower (3%). With respect to years of patronage, 34.9 percent of users answered for one to less than four years, 28.2 percent for less than a year, 19.9 percent for five to less than 10 years, 8.9 percent for 10 to less than 15 years, and 5.1 percent for 15 to less than 20 years. Only 3 percent have patronised the bank for more than 20 years.

Table 4.2: Summary of Respondents' Demography

Category	Frequency	% Percent
Gender		
Male	182	48.9
Female	190	51.1
Total	372	100
Age		
From 18 to less than 25 years	184	49.5
From 25 to less than 32 years	89	23.9
From 32 to less than 39 years	43	11.6
From 39 to less than 46 years	29	7.8
From 46 to less than 53 years	17	4.6
From 53 years and more	10	2.7
Total	372	100
Education Level		
High school and less.	11	3.0
Diploma	26	7.0
Bachelor's Degree	260	69.9
Master's Degree	55	14.8
PhDs	20	5.4
Other	0	0.0
Total	372	100
Years of dealing with your current bank		
Less than 1 year	105	28.2
From 1 to less than 5 years	130	34.9
From 5 to less than 10 years	74	19.9
From 10 to less than 15 years	33	8.9
From 15 to less than 20 years	19	5.1
20 years and more	11	3.0
Total	372	100

4.4 Non-response Bias Test

Non-response bias is a common error in assessing the characteristics of the sample due to the non-response of some respondents (Berg, 2010). According to Singer (2006), there is no minimum response rate below which the responses are necessarily biased and above which the responses are necessarily unbiased. Bias should be examined regardless of how small the possibility of non-response bias (Clottey & Grawe, 2014).

The main issue of non-response bias is that the views of people who do not respond to the questionnaire could be systematically different from the opinions of those who do respond (Sedgwick, 2014b). Therefore, when non-response bias exists, the outcome does not accurately reflect the views of the entire sample; in fact, it could lead to erroneous generalisation of the population. Accordingly, it is essential to consider this type of error before conducting the main analysis.

To minimise non-response bias, the researcher increased the response rate, as proposed by Salkind (2003) and Hair et al. (2010), and reminded the respondents through personal visits, phone calls, emails, consultation, and SMS (Dillman, 2011; Sekaran & Bougie, 2010a). The responses of early and late responses were then compared.

The non-response bias was assessed by separating the respondents into two groups, depending on their questionnaire return time, for all five variables (INQ, SYQ, E-SQ, continuous-use intention, and online banking performance). Levene's test for equality of variance was used to examine whether there were differences in the variances between the early respondents' group and late respondents' group.

Table 4.3: Group Descriptive Statistics for the Early and Late Respondents

Variables	Response	N	Mean	Std. Deviation	Std. Error
INQ	Early	185	3.649	0.572	0.042
	Late	187	3.617	0.601	0.044
CUI	Early	185	3.718	0.766	0.056
	Late	187	3.747	0.815	0.060
OBP	Early	185	3.811	0.377	0.028
	Late	187	3.773	0.458	0.034
E-SQ	Early	185	3.500	0.705	0.052
	Late	187	3.482	0.692	0.051
SYQ	Early	185	3.639	0.734	0.054
	Late	187	3.643	0.753	0.055

Note: INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality

The standard way to test for non-response bias is to compare the responses of those who respond to the questionnaire early to those who respond late. Late respondents are the non-respondent sample and presumed to be representatives of the non-respondents group (Wagner & Kemmerling, 2010).

Table 4.4: Statistically Significant Differences between Early and Late Responses

Independent Samples Test						
		Levene's Test for Equality of Variances		t-test for Equality of Means.		
		F	Sig.	t	df	Sig.
INQ	Early Response	.342	.559	.520	370	.603
	Late Response			.520	369.441	.603
CUI	Early Response	.257	.612	-.355-	370	.723
	Late Response			-.355-	369.024	.723
OBP	Early Response	2.148	.144	.867	370	.386
	Late Response			.868	358.031	.386
E-SQ	Early Response	.190	.663	.242	370	.809
	Late Response			.242	369.682	.809
SYQ	Early Response	.040	.842	-.050-	370	.960
	Late Response			-.050-	369.920	.960

Note: INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ; E- Service Quality; SYQ: System Quality

The Levene's test showed that the standard deviation and group mean for late and early respondents were not statistically different. As shown in Table 4.4, the test revealed no significant differences between early responses and late responses in information quality (t = .520, p = .603), continuous-use intention (t = -.355, p = .723), online banking performance (t = .868, p = .386), e-service quality (t = .224, p = .809), and system quality (t = -.050, p = .960). Pallant (2013) stated that if the p is equal or less than .05, the equality of variance assumption is violated, but if it is greater than 0.05, then the opposite is true. The findings showed that all p values were more than 0.05 for all variables, which means that the data should accurately reflect the opinions of online banking users in Jordanian commercial banks.

4.5 Descriptive Statistics

A descriptive analysis for data was carried out to describe the information quality, continuous-use intention, online banking performance, e-service quality, system quality from the perspective of external clients in Jordanian commercial banks. This research adopted the continuous-use intentions as mediator (as discussed in chapter Two under section 2.9.6). Descriptive analysis provides more detail about the responses through, for instance, mean and standard deviation. Mean is usually used to measure the central tendency, and it also gives the overall picture of the dataset (Sekaran & Bougie, 2010a). Standard deviation is a measure of dispersion that indicates the variability of the dataset. It is the square root of variance. Both mean and standard deviation are common descriptive statistics for ratio and interval scales, such as the five-point Likert used in this research. To explain the mean, the study followed the recommendation of Nik Muhammad et al. (2010), that a value of less than 2.33

(4/3 + 1) indicates a low level; 2.33 to 3.66 indicates moderate level; and 3.67 (5 - 4/3) and above indicates high level.

The result shows that Online banking performance had the highest mean, *M* = 3.791 of all the variables with the lowest standard deviation, *SD* = .420; while continuous-use intention scored the lowest mean, *M* = 3.372 with the standard deviation, *SD* = .790. These findings clearly refer to the gap among the external clients' perception of online banking performance and their continuance intention to use, which means that they continuance intention to use online banking are weak even though they perceive as important. The mean of continuous-use intention is less than the mean of online banking performance which is reflected in the major problem statement of the research.

System quality had the next highest mean, *M* = 3.640 with standard deviation, *SD* = 0.742; this result shows that external client's emphasis on system quality in Jordanian commercial banks. Information quality received mean, *M* = 3.638 with standard deviation, *SD* = 0.586. The findings also indicate the importance of information quality in the online banking system. Furthermore, Table 4.5 also shows that e-service quality had mean, *M* = 3.490 with standard deviation, *SD* = 0.697. The results clearly refer to that respondents recognise and emphasise the importance of e-service quality. Table 4.5 shows the descriptive analysis of the variables.

Table 4.5: Descriptive Analysis

Variable	N	Minimum	Maximum	Mean	St. deviation
INQ	372	1	5	3.638	0.58590
CUI	372	1	5	3.372	0.78993
OBP	372	1	5	3.791	0.41973
E-SQ	372	1	5	3.490	0.69771
SYQ	372	1	5	3.640	0.74228

Note: INQ; Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality. Scale: Strongly Disagree (1) to Strongly Agree (5).

4.6 Common Method Bias Test

Common method bias is the errors caused by the method of measurement rather than constructs that the instrument seeks to investigate. For example, collecting data using a single (common) method, such as online survey, may cause a systematic bias that either inflates or deflate responses. A study that has a significant common method bias is one in which the majority of variance (more than 50%) can be explained by one factor (Podsakoff et al., 2003a; Podsakoff et al., 2012b).

Harman's single factor test was used to see if a single factor can explain the majority of variance. If common method bias exists, a single factor will account for more than 50 percent of the model variance. In this research, an unrotated factor analysis of 50 items from all variables revealed that no single factor accounted more than 50 percent of the variance. While one factor did account for 34.39 percent of the total variance, it was still below the threshold, thus indicating the absence of common method bias. This is consistent with Podsakoff et al. (2003a) and Lowry & Gaskin (2014), who argued that common method bias exists if a single factor explains more than 50 percent of the variance.

Table 4.6: Unrotated Factor Analysis

Total Variance Explained						
	Initial Eigenvalues			**Extraction Sums of Squared Loading**		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	14.788	34.390	34.390	14.788	34.390	34.390
2	3.909	9.092	43.482			
3	3.000	6.978	50.460			
-	-	-	-			
-	-	-	-			
-	-	-	-			
-	-	-	-			
-						

Extraction Method: Principal Component Analysis.

4.7 Initial Data Examination, Screening and Preparation

Data examination, screening, and preparation are to ensure that the data are clean and ready for further statistical analysis. Data must be checked to ensure that they are usable, reliable, and valid, as well as to identify any violation of basic assumptions of multivariate techniques (Hair et al., 2010). There are several issues to address when cleaning data, including missing data, outliers (univariate and multivariate), normality, linearity, homoscedasticity, and multicollinearity. These are explained below.

4.7.1 Analysis of Missing Data

Missing data may be caused by questions that are ignored by respondents or irrelevant to their situation (Cheema, 2014). Missing data can cause several problems, such as reducing the amount of available data for analysis, which in turn reduces statistical power and reliability. Additionally, missing data may degrade data efficiency and return biased results (Kwak & Kim, 2017). How the missing values are treated will affect the results of analysis. The threshold for missing data varies. According to Schafer (1999) and cited by Dong & Peng (2013), missing data of 5 percent or less are acceptable. Bennett (2001) claimed that missing data of 10 percent or more would lead to biased results. Generally, if more than 10 percent of the responses for a particular variable or of a particular respondent are missing, that variable or respondent may be problematic.

Using SPSS v22, the researcher identified the missing data for all variables and respondents (cases). The results indicated that missing data made up less than 10 percent for every variable and case, which means that there were no problematic variables or cases in the dataset (Hair et al., 2010). The researcher filled the missing data using the median replacement method, which is the most appropriate replacement method, especially with Likert-type data (Lynch, 2007).

4.7.2 Analysis of Outliers

Outliers are extreme values that abnormally lie outside the overall distribution pattern of a variable (Kwak & Kim, 2017). Outliers significantly affect the estimation of statistics, resulting in overestimated or underestimated values e.g., by pulling the mean away from the median. How the outliers are treated will affect the results of data analysis. There are two types of outliers: outliers for individual variables (univariate), and outliers for the model (multivariate). Treating multivariate outliers will also remove univariate outliers (Ho, 2013; Hair et al., 2010). Mahalanobis D^2 was calculated using linear regression analysis in SPSS v22, followed by the computation of chi-square.

Given that 50 items were analysed, $\chi^2(49) = 86.66$, $p < 0.001$ (Tabachnick & Fidell, 2013). The criterion was 86.66, which means that any case with a Mahalanobis D^2 of 86.66 and above was a multivariate outlier and should be removed. The results indicate that there were no cases with a value of 86.66 and above (see Appendix 3). All cases were therefore included in the data analysis process.

4.7.3 Normality Test

After examining for outliers, the study assessed the normality of the data. Normality is a principal assumption and prerequisite for many inferential statistical techniques (Hair et al., 2010). Normality refers to the symmetrical, bell-shaped distribution of the data, with more frequencies in the middle and fewer frequencies towards the extremes (Gravetter & Wallnau, 2006). According to Coakes & Steed

(2007), the normality assumption can be explored graphically (histograms, stem-and-leaf plots, boxplots, normal probability plots, detrended normal plots) and statistically (Kolmogorov-Smirnov statistic with Lilliefors significance level, Shapiro-Wilk statistic, and skewness and kurtosis).

Normality can be assessed to some extent by obtaining skewness and kurtosis values (Hair, 2010b; Coakes & Steed, 2007; Orcan, 2020). Therefore, this study assessed the normality of the data by obtaining the skewness and kurtosis for every item of the instrument. The results were analysed using the guidelines provided by Kline (2011): the skewness value should be between -3 and 3, while kurtosis between -10 and 10. Multivariate normality means that both the individual variables and overall model are normal (Hair et al., 2003; Tabachnick & Fidell, 2013). Nevertheless, Tabachnick & Fidell (2013) indicate that deviation from normality data of Skewness and Kurtosis mostly do not make a fundamental difference in the analysis when the size of samples is over 200.

As Table 4.7 shows, almost all items were skewed, and no perfectly normal distribution was observed. Nonetheless, the values of the skewness and kurtosis for all items were within the acceptable range. Skewness is within the range of -.842 to .326 while kurtosis is within the range of -1.346 to 2.461. Therefore, normal distribution could be assumed, and parametric tests could be used for data analysis.

Table 4.7: Normality Test

Item	Mean	Std. Deviation	Skewness	Kurtosis
INQ1: The website provides relevant information.	3.67	.827	-.627-	.878
INQ10: The information provided on the website is based on facts.	3.66	.809	-.204-	-.100-
INQ11: The information provided on the website has a good reputation for quality.	3.53	.798	.013	.029
INQ12: The information presented on the website is protected against unauthorised access.	3.70	.737	.043	-.452-
INQ13: The information presented on the website is easy to understand.	3.64	.836	-.305-	-.022-
INQ2: The website provides an appropriate amount of information.	3.64	.869	-.440-	.240
INQ3: The information provided on the website is accurate and free-of-error.	3.49	.789	.326	-.061-
INQ4: The information provided on the website is consistent and useful.	3.63	.760	-.230-	.158
INQ5: The information provided on the website is complete enough for the client's needs.	3.40	.880	-.255-	.354
INQ6: The website provides believable information.	3.55	.795	-.199-	.261
INQ7: The website is accessible when needed.	3.89	.944	-.842-	.592
INQ8: The bank website saves the client’s time to get exactly the needed information.	3.78	.972	-.530-	-.061-
INQ9: The information provided on the website is easily interpretable.	3.76	.967	-.501-	-.140-
CUI1: I intend to continue using online banking in the future.	3.67	.972	-.423-	-.197-
CUI2: I intend to take full advantage of online banking.	3.58	.944	-.300-	-.398-
CUI3: I will use online banking regularly in the future.	3.73	.986	-.396-	-.419-
CUI4: I will frequently use online banking in the near future.	3.72	.926	-.553-	.135
CUI5: I intend to continue using online banking than using any alternative means (traditional banking).	3.63	.997	-.352-	-.392-
CUI6: The probability that I will use online banking again is high.	3.66	.659	.268	-.496-
CUI7: I have positive attitudes toward using the online banking system.	3.86	.742	.105	-.918-
CUI8: The likelihood that I would recommend the online banking system to friends, relatives, or others.	3.79	.644	-.020-	-.227-

‘Table 4.7, Continued’

Item	Mean	Std. Deviation	Skewness	Kurtosis
OBP1: I prefer visiting the branch instead of using online banking services to do my transactions.	3.76	.670	.007	.022
OBP10: I feel at risk while making transactions through the online banking system.	3.90	.772	-.101-	-.527-
OBP11: Online banking systems work as advertised.	3.79	.641	-.582-	1.582
OBP12: Online banking systems are exposed to illegal tampering.	3.95	.735	.031	-1.037-
OBP13: The service delivered through the e-banking systems is quick.	4.05	.758	-.454-	.040
OBP14: My high confidence in online banking services is making my relationship with the bank closer.	4.16	.743	-.497-	-.306-
OBP15: Online banking services are available 24/7 and anywhere in the world.	3.78	.686	-.801-	2.461
OBP16: I am satisfied with the transaction processed via online banking services.	3.88	.814	.155	-1.346-
OBP2: Online banking system periodically sends warning notifications to my account to avoid fraudulent activities.	3.84	.688	.117	-.688-
OBP3: I can easily complete any transactions through the online banking service channels.	3.42	.848	-.199-	.065
OBP4: Online banking service is secure and safe from any fraud or hacking.	3.38	.896	-.195-	.116
OBP5: The security systems of the online banking services send notifications to confirm the transactions are performed by me.	3.70	.808	-.108-	-.045-
OBP6: The use of online banking services saves time and effort.	3.51	.907	-.207-	-.188-
OBP7: Online banking services are provided in various languages.	3.53	.848	-.178-	-.198-
OBP8: Online banking services do not allow intruders to access my accounts.	3.27	.813	.106	.346
OBP9: Online banking services have low fees/charges.	3.65	.832	-.308-	.005

'Table 4.7, Continued'

Item	Mean	Std. Deviation	Skewness	Kurtosis
E-SQ1: The bank makes accurate promises on the website to the client regarding order delivery and item availability.	3.73	.993	-.656-	.056
E-SQ2: The website deals with problems promptly, as it tells the customer what to do if the transaction is not processed.	3.66	.883	-.590-	.612
E-SQ3: The website is safe from intrusion, as the system protects client information.	3.65	.854	-.001-	-.329-
E-SQ4: The bank assists the client through telephone or online representatives if there is a problem regarding the website.	3.58	.897	-.477-	.114
E-SQ5: The bank continuously processes the technical functioning of the website.	3.61	.900	-.570-	.371
E-SQ6: The bank compensates the client for problems caused by the website.	3.61	.879	-.495-	.173
E-SQ7: The customer can access the website quickly and it is easy to use.	3.67	.827	-.627-	.878
SYQ1: The website system is easy to use.	3.66	.809	-.204-	-.100-
SYQ2: The website system has the flexibility and portability to accomplish banking transactions to the fullest.	3.53	.798	.013	.029
SYQ3: The website system is trustworthy.	3.70	.737	.043	-.452-
SYQ4: The website system is easily accessible to precisely do what the client wants.	3.64	.836	-.305-	-.022-
SYQ5: The website system provides up to date information.	3.64	.869	-.440-	.240
SYQ6: The response time of the website system is acceptable.	3.49	.789	.326	-.061-

Note: INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality

4.7.4 Linearity Test

The linearity assumption is supported by a normal probability plot of the regression-standardised residual, as indicated by various authors. Figures 4.1 and 4.2 show the results of a linearity test for each of the continuous-use intention as mediator and online banking performance as dependent variable. The figures below indicate that all of the points are in a fairly straight diagonal line, that the normality assumptions are achieved, and that there are no significant deviations from normality.

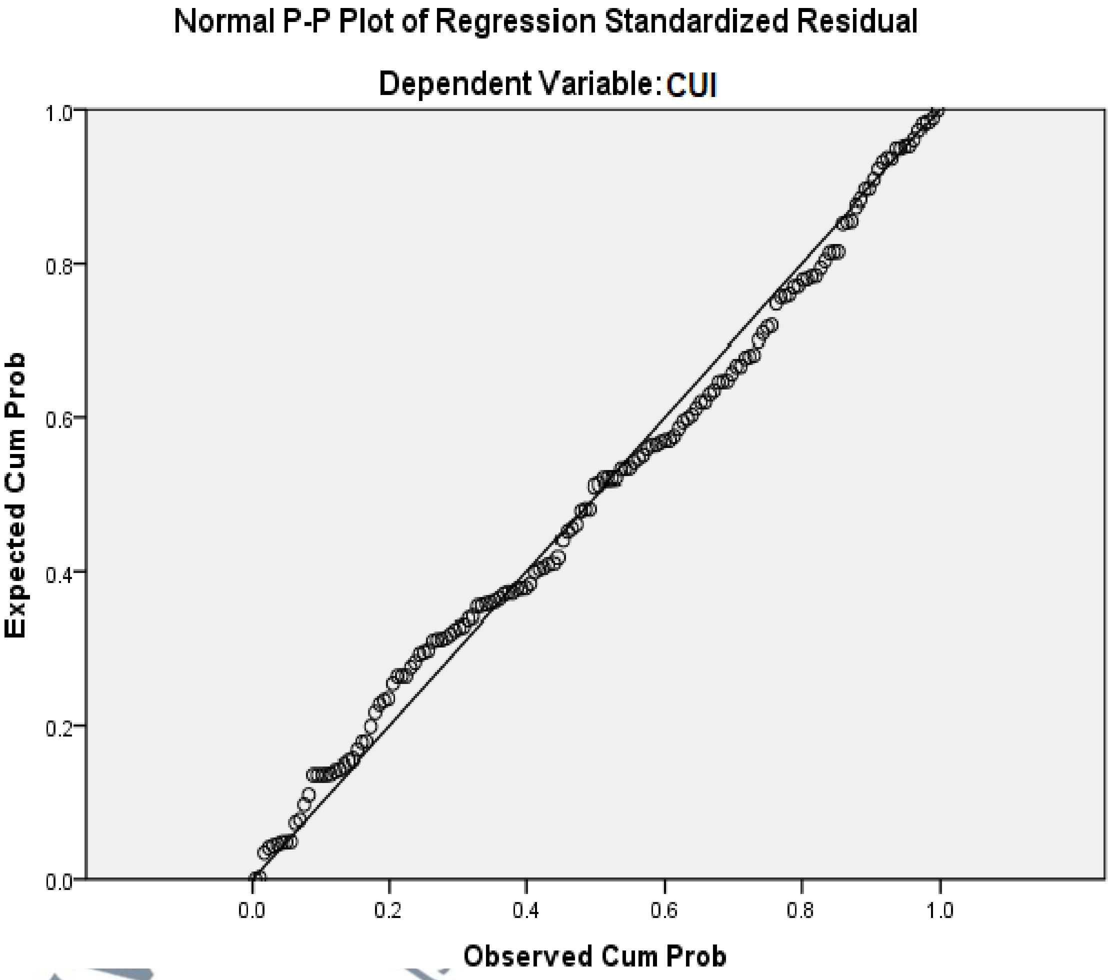

Figure 4.1: Test of Linearity for Continuous-Use Intention (CUI)

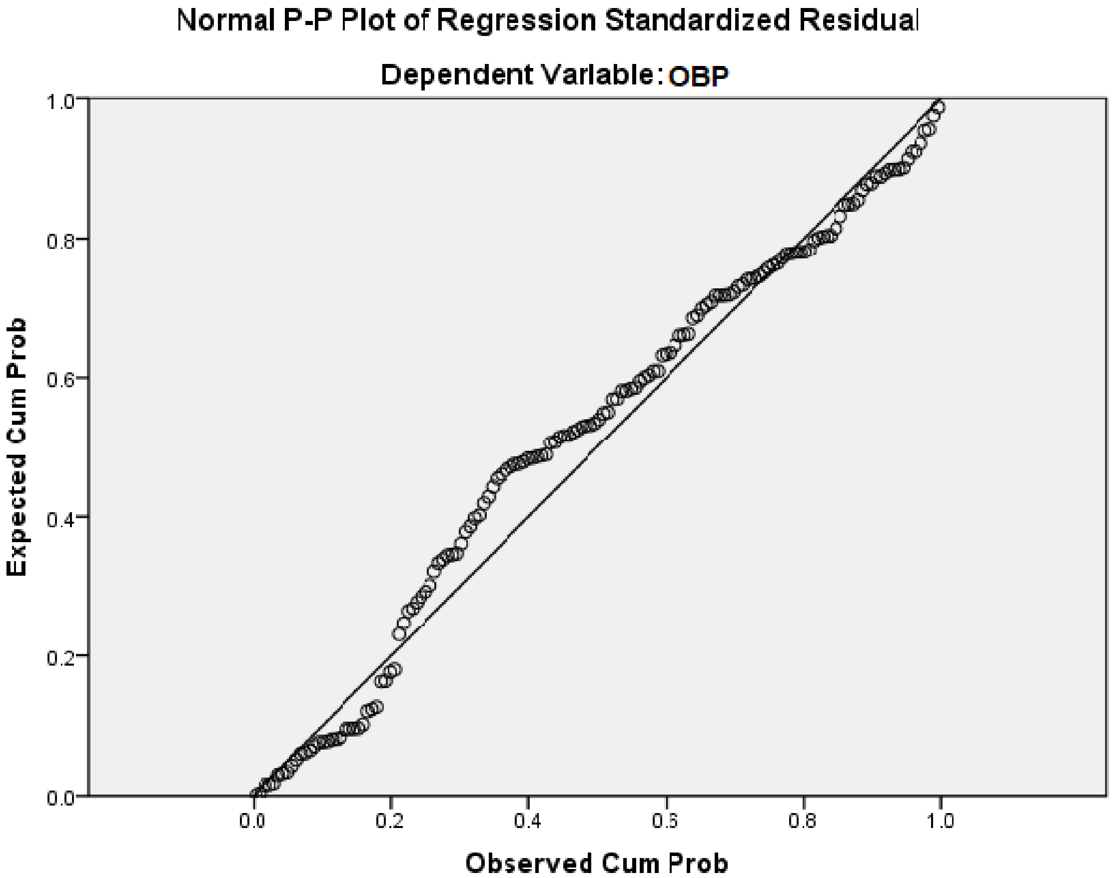

Figure 4.2: Test of Linearity for Online Banking Performance (OBP)

4.7.5 Homoscedasticity Test

The scatter plot is used to conduct the homoscedasticity test, as suggested by studies in the literature (e.g. Hair et al., 2010; Pallant, 2013). For both continuous-use intention and online banking performance, scatter plot diagrams of standardised residuals are utilised to test homoscedasticity. Figures 4.3 and 4.4 show two scatter plots that describe the results of this test.

The two figures illustrate that there is no systematic structure, such as curvilinear or residuals, on one side. As a result, the homoscedasticity assumption was met.

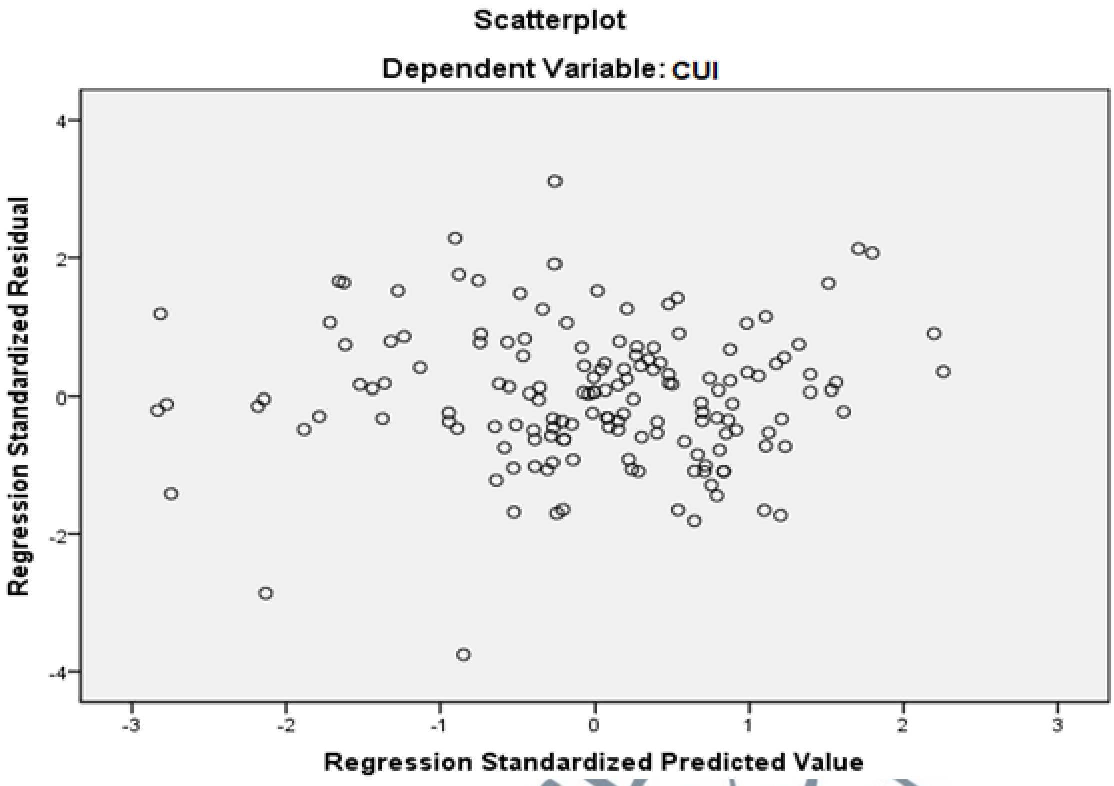

Figure 4.3: Homoscedasticity Test for Continuous-Use Intention (CUI)

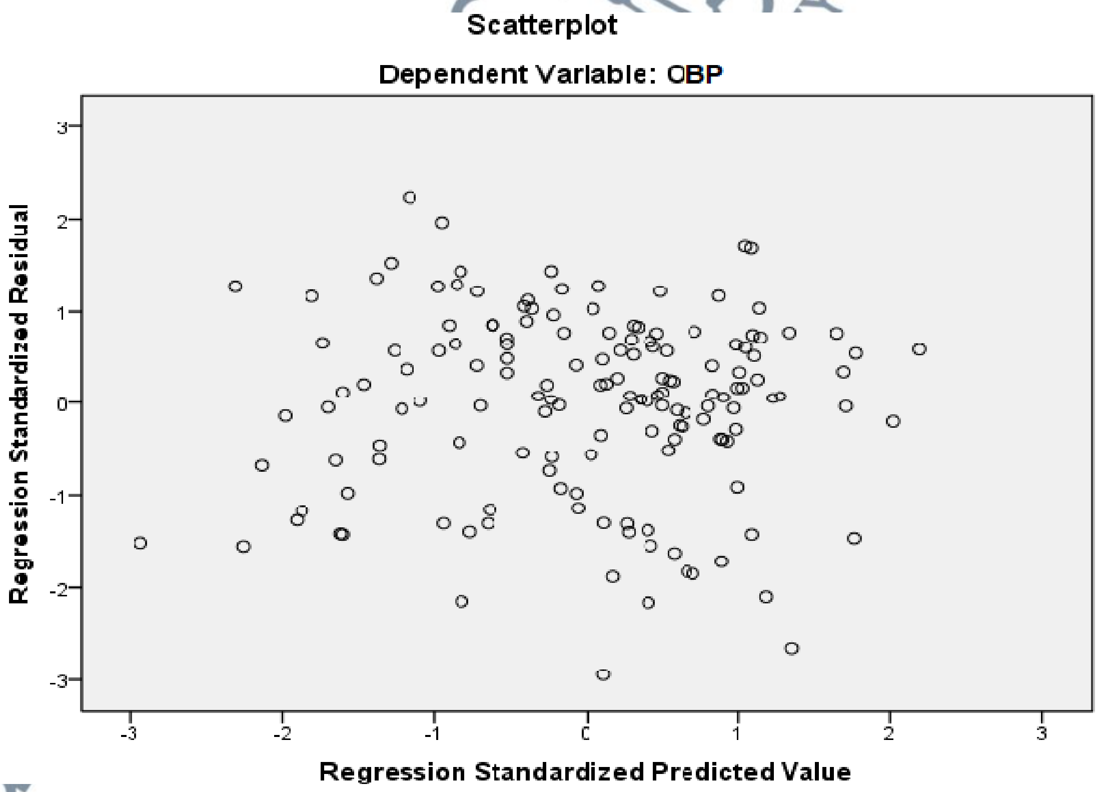

Figure 4.4: Homoscedasticity Test for Online Banking Performance (OBP)

4.7.6 Multicollinearity Test

Multicollinearity exists when the independent variables are greatly correlated to each other (Hair, 2010b; Hair et al., 2014b; Tabachnick & Fidell, 2013). When multicollinearity is high, the standard error of the regression coefficient increases, so the statistical significance of these coefficients becomes less reliable. Multicollinearity can be examined by calculating the variance inflation factor (VIF) and tolerance for each independent variable. The acceptable threshold for VIF is more than 0.1 and for tolerance is less than 10 (Hair et al., 2010; Hair et al., 2014b; Pallant, 2010). In this study, multicollinearity was tested by examining the correlation matrix, tolerance, and VIF of the independent variables. Multicollinearity exists when the correlation between independent variables is higher than 0.9 (Hair et al., 2010; Hair et al., 2014b). However, Pallant (2010) suggested a correlation coefficient of above 0.7 as a threshold for multicollinearity. The results showed that none of the exogenous variables were highly intercorrelated. Table 4.8 shows that the correlation values were well below the threshold of 0.7. Therefore, no multicollinearity was detected.

Table 4.8: Correlations among the Exogenous Variables

Variables	INQ	CUI	E-SQ	SYQ
INQ	**1**			
CUI	.361	**1**		
E-SQ	.603	.378	**1**	
SYQ	.659	.356	.599	**1**

Note: INQ: Information Quality; CUI: Continuous-Use Intention; E-SQ: E-Service Quality; SYQ: System Quality

Multicollinearity was also tested using tolerance and VIF tests, as they are the most important and reliable tools to detect multicollinearity (Hair et al., 2010; Hair et al., 2014b). Table 4.9 indicates that tolerance ranged between 0.492 and 0.820, which are substantially greater than 0.1, while VIF ranged from 1.219 to 2.034, which are considerably less than 10. Consistent with Hair et al. (2010) and Hair et al. (2014a), tolerance values below 0.10 and VIF values above 10 indicate high collinearity. Therefore, the results showed that multicollinearity did not exist in the study data.

Table 4.9: Multicollinearity Test based on Tolerance and VIF Values.

	Collinearity Statistics	
Variables	**Tolerance**	**VIF**
INQ	.492	2.034
CUI	.820	1.219
E-SQ	.548	1.824
SYQ	.496	2.016

Note: INQ: Information Quality; CUI: Continuous-Use Intention; E-SQ: E-Service Quality: SYQ: System Quality

4.8 Assessment of PLS-SEM Outcome

This section reports the findings of the factor analysis. The outer model indicated the unidimensionality of the research variables. As explained in Chapter Three, all items were adapted from previous studies. The validity and reliability of the constructed measures were confirmed, the structural models were evaluated, and the relationships between the latent variables were examined.

After examining and screening the data, the next stage was to assess the outer model and inner model (Hair et al., 2013a; Esposito Vinzi et al., 2010). PLS-SEM was used to evaluate the outer model (measurement model) and the inner model (structural model). Smart PLS 3.0, developed by Ringle et al. (2014), was employed to determine the paths between the constructs in the model.

Before conducting PLS-SEM, the conceptual framework should be clearly defined first. Before doing so, it is necessary to determine whether the indicators are formative or reflective, because the analysis of a reflective measurement model is quite different than that of a formative measurement model (Hair et al., 2013a; Lowry & Gaskin, 2014). In this research, the measurement model was reflective.

The model did not include any second-order constructs; all constructs were treated as first-order. The model comprised four exogenous latent variables: three independent variables (INQ, SYQ, and E-SQ,) and a mediating variable (continuous-use intention). The endogenous variables were the mediating variable (continuous-use intention) and the dependent variable (online banking performance).

4.8.1 The Measurement Model

The first stage in PLS-SEM analysis is the evaluation of the measurement model (outer model). The measurement model is concerned with the relationship between the constructs and their items, that is, the theoretical fit of the items to the construct that they represent. In other words, analysing the outer model will confirm whether the questionnaire items adequately represent the construct, indicating the validity and reliability of the model.

4.8.1.1 Indicator Reliability

Validity and reliability are the two main criteria in assessing the outer model (Hair et al., 2013a; Ramayah et al., 2011). The inference of the relationships between the constructs in the inner model depends on the validity and reliability of the outer model. The outer model fit can be evaluated by looking at three indicators. Firstly, composite reliability (CR), which indicates the reliability of individual items, that is, internal consistency and indicator reliability. Secondly, average variance extracted (AVE), which indicates the convergent validity of the constructs. Thirdly, the Fornell-Larcker criterion and outer loadings, which indicate discriminant validity.

4.8.1.2 Internal Consistency Reliability

Internal consistency measures the similarity of scores between items of the same construct. According to Hair et al. (2013a), it measures whether the items measuring the same construct produce similar scores. In this research, internal consistency was evaluated using CR.

As Hair et al. (2013a) suggested, contrary to Cronbach's alpha, composite reliability does not assume that all items of a construct have equal factor loadings. Composite reliability ranges between 0 and 1. The threshold is 0.60 (Henseler et al., 2009), but a value of 0.70 and above is more desirable (Hair et al., 2014a). A composite reliability value of between 0.60 and 0.70 indicates average internal consistency, while a value between 0.70 and 0.90 is more satisfactory (Hair et al., 2014a; Hair et al., 2019; Nunnally & Bernstein, 1994).

Accordingly, Cronbach's alpha and CR values for all constructs were tested. Table 4.10 shows that all Cronbach's alpha and CR values exceeded the recommended threshold of 0.7 (Henseler et al., 2009; Hair et al., 2013a; Hair et al., 2019). The composite reliability values ranged from 0.895 to 0.943, indicating the reliability of the measurement model.

4.8.1.3 Convergent Validity

Convergent validity is the degree to which measures of the same construct are theoretically correlated with each other (Henseler et al., 2009). It determines the degree of correlation between measures of the same construct (Hair et al., 2013a). To determine the convergence of construct measurements, the average variance extracted (AVE) was calculated, and its threshold is 0.50 and more (Hair et al., 2012 Hair et al., 2019; Henseler et al., 2009). An AVE of 0.50 indicates adequate convergent validity.

In other words, the latent construct describes 50 percent of the variance of its items and shows adequate convergent validity (Hair et al., 2013a; Hair et al., 2019). In this research, convergent validity was tested using AVE. Table 4.10 shows that overall, the AVE values ranged from 0.416 to 0.678. The AVE for all constructs exceeded the threshold of 0.50 (Hair et al., 2012; Hair et al., 2019; Henseler et al., 2009), except for online banking performance (OBP), whose AVE was 0.416. Nonetheless, Fornell & Larcker (1981) mentioned even if AVE is less than .50, but the CR was greater than 0.60, it can be concluded that convergent validity was established (Hair et al., 2013a).

Table 4.10: Loadings, Reliability and Convergent Validity Values

Variables	Items	Loading	Indicator Reliability	Cronbach's Alpha	CR	AVE	Convergent Validity?
INQ	**INQ1:** The website provides relevant information.	0.780	0.608	0.925	0.937	0.599	Yes
	INQ10: The information provided on the website is based on facts.	0.803	0.645				
	INQ11: The information provided on the website has a good reputation for quality.	0.811	0.658				
	INQ12: The information presented on the website is protected against unauthorised access.	0.770	0.593				
	INQ13: The information presented on the website is easy to understand.	0.815	0.664				
	INQ2: The website provides an appropriate amount of information.	0.752	0.566				
	INQ3: The information provided on the website is accurate and free-of-error.	0.704	0.496				
	INQ4: The information provided on the website is consistent and useful.	0.774	0.599				
	INQ5: The information provided on the website is complete enough for the client's needs.	0.778	0.605				
	INQ9: The information provided on the website is easily interpretable.	0.744	0.554				
CUI	**CUI1:** I intend to continue using online banking in the future.	0.849	0.721	0.931	0.943	0.675	Yes
	CUI2: I intend to take full advantage of online banking.	0.849	0.721				
	CUI3: I will use online banking regularly in the future.	0.840	0.706				
	CUI4: I will frequently use online banking in the near future.	0.851	0.724				
	CUI5: I intend to continue using online banking than using any alternative means (traditional banking).	0.744	0.554				
	CUI6: The probability that I will use online banking again is high.	0.826	0.682				
	CUI7: I have positive attitudes toward using the online banking system.	0.819	0.671				
	CUI8: The likelihood that I would recommend the online banking system to friends, relatives, or others.	0.791	0.626				

'Table 4.10, Continued'

Variables	Items	Loading	Indicator Reliability	Cronbach's Alpha	CR	AVE	Convergent Validity?
OBP	**OBP11:** Online banking systems work as advertised.	0.626	0.392	0.873	0.895	0.416	Yes
	OBP12: Online banking systems are exposed to illegal tampering.	0.589	0.347				
	OBP13: The service delivered through the e-banking systems is quick.	0.693	0.480				
	OBP14: My high confidence in online banking services is making my relationship with the bank closer.	0.666	0.444				
	OBP15: Online banking services are available 24/7 and anywhere in the world.	0.641	0.411				
	OBP3: I can easily complete any transactions through the online banking service channels.	0.711	0.506				
	OBP4: Online banking service is secure and safe from any fraud or hacking.	0.653	0.426				
	OBP5: The security systems of the online banking services send notifications to confirm the transactions are performed by me.	0.614	0.377				
	OBP6: The use of online banking services saves time and effort.	0.671	0.450				
	OBP7: Online banking services are provided in various languages.	0.618	0.382				
	OBP8: Online banking services do not allow intruders to access my accounts.	0.632	0.399				
	OBP9: Online banking services have low fees/charges.	0.620	0.384				
E-SQ	**E-SQ1:** The bank makes accurate promises on the website to the client regarding order delivery and item availability.	0.842	0.709	0.931	0.943	0.675	Yes
	E-SQ2: The website deals with problems promptly, as it tells the customer what to do if the transaction is not processed.	0.821	0.674				
	E-SQ3: The website is safe from intrusion, as the system protects client information.	0.824	0.679				
	E-SQ4: The bank assists the client through telephone or online representatives if there is a problem regarding the website.	0.791	0.626				
	E-SQ5: The bank continuously processes the technical functioning of the website.	0.827	0.684				
	E-SQ6: The bank compensates the client for problems caused by the website.	0.771	0.594				
	E-SQ7: The customer can access the website quickly and it is easy to use.	0.857	0.734				

‘Table 4.10, Continued’

Variables	Items	Loading	Indicator Reliability	Cronbach’s Alpha	CR	AVE	Convergent Validity?
SYQ	**SYQ1:** The website system is easy to use.	0.822	0.676	0.905	0.927	0.678	Yes
	SYQ2: The website system has the flexibility and portability to accomplish banking transactions to the fullest.	0.854	0.729				
	SYQ3: The website system is trustworthy.	0.796	0.634				
	SYQ4: The website system is easily accessible to precisely do what the client wants.	0.855	0.731				
	SYQ5: The website system provides up to date information.	0.797	0.635				
	SYQ6: The response time of the website system is acceptable.	0.814	0.663				

Note: INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality

4.8.1.4 Discriminant Validity

Discriminant validity indicates how a construct is indeed different from another construct. In other words, the items of different constructs are theoretically not associated with each other; in fact, they are unrelated to each other (Churchill, 1979; Hair et al., 2013a). The most common method of evaluating discriminant validity is the Fornell-Larcker criterion (Hair et al., 2013a). Another method is the cross-loading test, which is deemed more lenient because it could show discriminant validity in more constructs.

Discriminant validity is obtained when the square root of AVE of each construct is higher than its highest correlation to other constructs (Hair et al., 2013a; Henseler et al., 2015; Henseler et al., 2009). Discriminant validity was evaluated by comparing the square root of AVE of each construct to its correlation coefficients, as shown in the correlation matrix. Table 4.11 presents the results of the Fornell-Larcker criterion test and the square root of the constructs. The square roots of AVE (bolded) were greater than each construct's highest correlation to other constructs. Therefore, discriminant validity was found for all constructs (Hair et al., 2013a; Henseler et al., 2015; Henseler et al., 2009).

Table 4.11: Discriminant Validity

Variables	INQ	CUI	OBP	E-SQ	SYQ
INQ	**0.774**				
CUI	0.332	**0.822**			
OBP	0.504	0.380	**0.645**		
E-SQ	0.581	0.383	0.437	**0.819**	
SYQ	0.615	0.367	0.501	0.603	**0.823**

Note: INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality

Discriminant validity, as Hair et al. (2013a) suggested, can also be evaluated using the items' outer loadings. They explained that the discriminant validity is confirmed when each item's outer loading on the construct is greater than all its cross-loading to other constructs. Accordingly, Table 4.12 confirms discriminant validity because the loadings were greater than 0.50, and no factors had higher loadings than on the one it intended to measure.

Table 4.12: Cross Loading of the Items

Items	INQ	BIU	PER	E-SQ	SYQ
INQ1: The website provides relevant information.	**0.7802**	0.2397	0.3543	0.4398	0.486
INQ10: The information provided on the website is based on facts.	**0.8032**	0.2688	0.4518	0.4679	0.4926
INQ11: The information provided on the website has a good reputation for quality.	**0.8115**	0.3149	0.4095	0.5169	0.5482
INQ12: The information presented on the website is protected against unauthorised access.	**0.7699**	0.2351	0.4286	0.4141	0.4792
INQ13: The information presented on the website is easy to understand.	**0.8153**	0.2322	0.4274	0.4474	0.5359
INQ2: The website provides an appropriate amount of information.	**0.7518**	0.2412	0.3055	0.4184	0.4729
INQ3: The information provided on the website is accurate and free-of-error.	**0.7043**	0.3014	0.3532	0.4231	0.3821
INQ4: The information provided on the website is consistent and useful.	**0.7737**	0.2573	0.3756	0.4672	0.426
INQ5: The information provided on the website is complete enough for the client's needs**.**	**0.7776**	0.2606	0.38	0.4808	0.4549
INQ9: The information provided on the website is easily interpretable.	**0.7436**	0.2059	0.3843	0.4073	0.4673
CUI1: I intend to continue using online banking in the future.	0.3108	**0.8489**	0.3228	0.324	0.3075
CUI2: I intend to take full advantage of online banking.	0.3269	**0.8485**	0.3308	0.318	0.3355
CUI3: I will use online banking regularly in the future.	0.2625	**0.8400**	0.2621	0.3258	0.3088
CUI4: I will frequently use online banking in the near future.	0.2526	**0.8506**	0.3128	0.3241	0.2934
CUI5: I intend to continue using online banking than using any alternative means (traditional banking).	0.1371	**0.7441**	0.2905	0.23	0.1744
CUI6: The probability that I will use online banking again is high.	0.2967	**0.8258**	0.2948	0.348	0.2875
CUI7: I have positive attitudes toward using the online banking system.	0.2866	**0.8193**	0.3777	0.3255	0.3527
CUI8: The likelihood that I would recommend the online banking system to friends, relatives, or others.	0.2727	**0.7909**	0.2903	0.3099	0.3186

‘Table 4.12, Continued’

Items	INQ	CUI	OBP	E-SQ	SYQ
OBP11: Online banking systems work as advertised.	0.2985	0.2373	**0.6260**	0.3124	0.3974
OBP12: Online banking systems are exposed to illegal tampering.	0.2985	0.181	**0.5889**	0.1827	0.2104
OBP13: The service delivered through the e-banking systems is quick.	0.3596	0.2922	**0.6935**	0.2705	0.3557
OBP14: My high confidence in online banking services is making my relationship with the bank closer.	0.3039	0.3001	**0.6659**	0.3298	0.345
OBP15: Online banking services are available 24/7 and anywhere in the world.	0.3261	0.2352	**0.6412**	0.3718	0.3513
OBP3: I can easily complete any transactions through the online banking service channels.	0.4184	0.2175	**0.7106**	0.3681	0.4161
OBP4: Online banking service is secure and safe from any fraud or hacking.	0.3567	0.237	**0.6531**	0.2714	0.3232
OBP5: The security systems of the online banking services send notifications to confirm the transactions are performed by me.	0.2639	0.1792	**0.6135**	0.2286	0.2437
OBP6: The use of online banking services saves time and effort.	0.3136	0.4098	**0.6713**	0.2635	0.3238
OBP7: Online banking services are provided in various languages.	0.2708	0.2132	**0.6177**	0.2047	0.2721
OBP8: Online banking services do not allow intruders to access my accounts.	0.3191	0.1796	**0.6322**	0.268	0.2516
OBP9: Online banking services have low fees/charges.	0.3415	0.2079	**0.6195**	0.2523	0.3191
E-SQ1: The bank makes accurate promises on the website to the client regarding order delivery and item availability.	0.5347	0.3233	0.3713	**0.8418**	0.5281
E-SQ2: The website deals with problems promptly, as it tells the customer what to do if the transaction is not processed.	0.4926	0.2953	0.3144	**0.8208**	0.5126
E-SQ3: The website is safe from intrusion, as the system protects client information.	0.5355	0.3016	0.4289	**0.8236**	0.4685
E-SQ4: The bank assists the client through telephone or online representatives if there is a problem regarding the website.	0.3646	0.3243	0.2784	**0.7906**	0.4417
E-SQ5: The bank continuously processes the technical functioning of the website.	0.4678	0.3172	0.4126	**0.8265**	0.5113

‘Table 4.12, Continued’

Items	INQ	CUI	OBP	E-SQ	SYQ
E-SQ6: The bank compensates the client for problems caused by the website.	0.3561	0.2493	0.228	**0.7712**	0.4129
E-SQ7: The customer can access the website quickly and it is easy to use.	0.5304	0.3687	0.4082	**0.8565**	0.5582
SYQ1: The website system is easy to use.	0.5038	0.2795	0.3836	0.4613	**0.8224**
SYQ2: The website system has the flexibility and portability to accomplish banking transactions to the fullest.	0.4838	0.3099	0.4315	0.477	**0.8544**
SYQ3: The website system is trustworthy.	0.4973	0.3787	0.4647	0.4644	**0.7961**
SYQ4: The website system is easily accessible to precisely do what the client wants.	0.5318	0.2579	0.4046	0.4945	**0.8546**
SYQ5: The website system provides up to date information.	0.5586	0.2899	0.5347	0.5387	**0.7966**
SYQ6: The response time of the website system is acceptable.	0.4661	0.2751	0.4926	0.5504	**0.8144**

Note. The bold values indicate the items that belong to the column’s construct.
INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality.

After confirming the validity and reliability of the measurement model, the next stage was to evaluate the inner model (structural model). While the original model was adapted from previous studies, it must still be reviewed since the evaluation of the outer model resulted in the deletion of seven items. None of the constructs were removed, and each construct still had a sufficient number of items (Hair et al., 2012; (Hair et al., 2020).

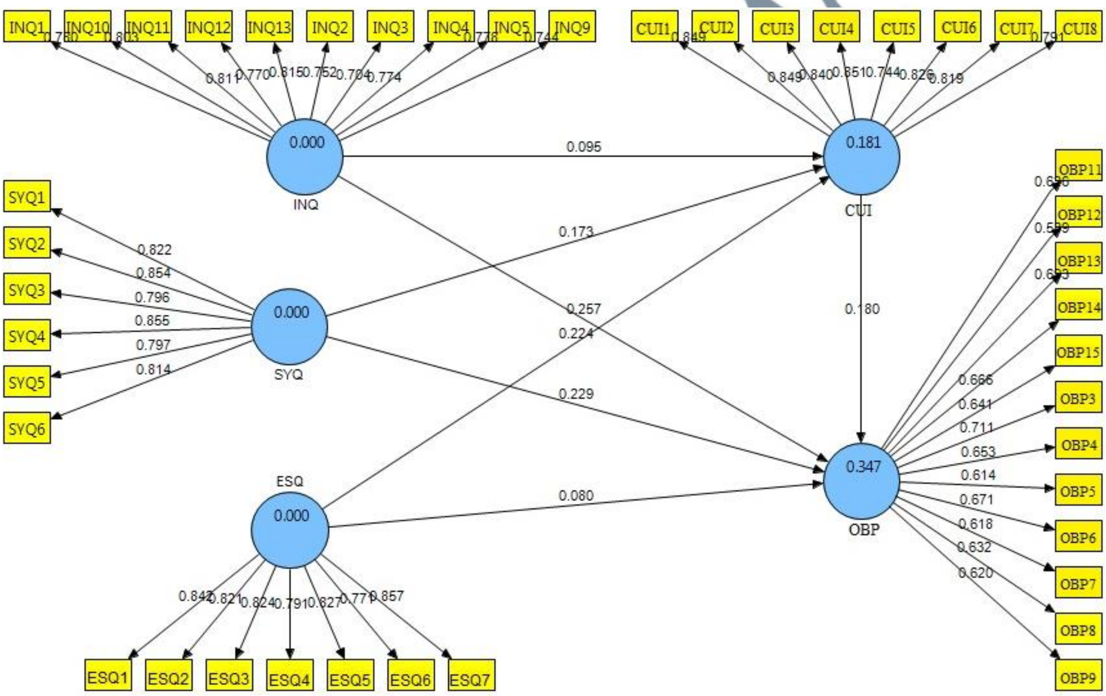

Figure 4.5: Measurement Model

4.8.2 The Structural Model

As indicated earlier, once the outer model (measurement model) is examined and the validity and reliability of the model are discussed, the next stage was to evaluate the structural model (inner model) results. Evaluation of the structural model involves examining the inner model's predictive abilities and the relationships between the constructs. According to Hair et al. (2013a) and Hair et al. (2019), the main criteria for assessing a structural model in PLS-SEM are coefficient of determination (R^2), predictive relevance (Q^2), significance of path coefficients, and effect size (f^2). In this research, the structural model was systematically analysed to present a detailed picture of the results and to comprehensively test all formulated hypotheses. The PLS-SEM algorithm estimated the size of the path coefficients, while the significance of the relationships was tested using the PLS-SEM bootstrapping method in Smart PLS 3.0. The number of cases was set according to the original sample (372), and the bootstrapping subsamples were set to 5,000 (Henseler et al., 2009; Hair et al., 2012; Hair et al., 2011; Hair et al., 2013a).

4.8.2.1 Evaluation of Coefficient of Determination (R^2)

The most common measure for assessing a structural model is the coefficient of determination (R^2) of endogenous latent variables (Hair et al., 2013a; Hair et al., 2019). As Cohen (2013) reported, R^2 values of 0.27, 0.13, and 0.02 are respectively strong, moderate, and weak effect sizes. The findings in Figure 4.5 revealed that the R^2 of continuous-use intention (0.181) was moderate and online banking performance (0.347) was strong.

As shown in Table 4.13, the combined R^2 of all three exogenous variables (INQ, SYQ, and E-SQ) in the model accounted for 18 percent of the variance in the mediating variable, continuous-use intention. Likewise, the overall R^2 value for all four exogenous variables (INQ, SYQ, E-SQ, and continuous-use intention) explained 35 percent of the variance in the endogenous variable (online banking performance). Therefore, the R^2 of the endogenous latent variables on online banking performance (0.35) and on continuous-use intention (0.18) indicated that the model had substantial predictive validity.

Table 4.13: R-Square of the Endogenous Latent Variables

Endogenous Variables	R^2
Online Banking Performance	0.35
Continuous-Use Intention	0.18

Note: CUI: Continuous-Use Intention; OBP: Online Banking Performance

4.8.2.2 Estimation of Path Coefficients and T-statistics

4.8.2.2.1 Direct Relationships

The study estimated the direct relationships between the independent variables (INQ, SYQ, and E-SQ) and dependent variable online banking performance, as represented by hypotheses 1-3 (H1 to H3). Figures 4.6 and 4.7 and Table 4.14 show the path coefficients, *t*-statistics, and *p*-values of the direct relationship model.

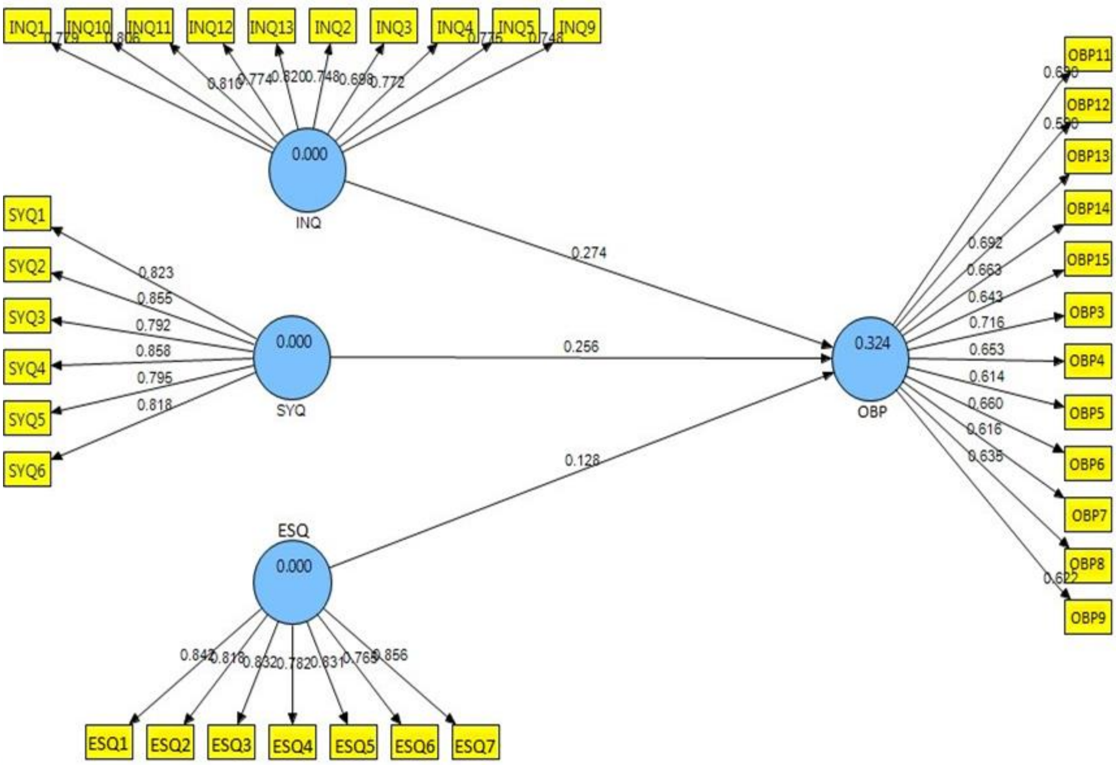

Figure 4.6: PLS Algorithm Direct Relationship (INQ, SYQ, E-SQ, and OBP)

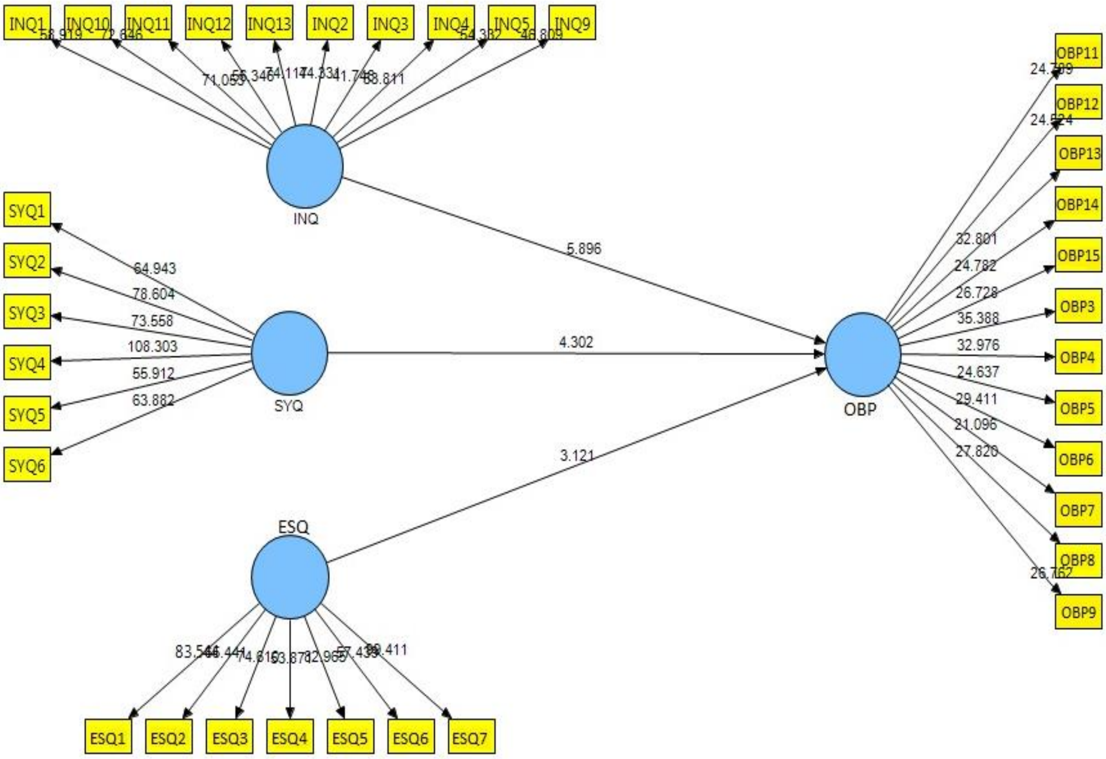

Figure 4.7: PLS-SEM Bootstrapping Direct Relationship (INQ, SYQ, E-SQ, and OBP)

Using PLS-SEM algorithm and bootstrapping, Figure 4.6 presents the path coefficient from the independent variables to the dependent variable. The findings showed that all independent variables had positive path coefficients towards the dependent variable. The bootstrapping findings in Figure 4.7 revealed that the association between all independent variables and the dependent variable is significant, $p < 0.001$. Therefore, the hypotheses were accepted. The results suggest that poor website quality is a major impediment of online banking performance. Table 4.14 shows the path coefficients, *t*-statistics, and *p*-values.

Table 4.14: Direct Relationship (INQ, SYQ, E-SQ, and OBP)

Hypothesis	Path	Path Coefficient	Standard Error	T-Statistics	P-Value	Decision
H1	INQ -> OBP	0.274***	0.047	5.8961	0.000	Supported
H2	SYQ -> OBP	0.256***	0.060	4.3018	0.000	Supported
H3	E-SQ ->OBP	0.128***	0.041	3.1208	0.000	Supported

*: p<0.05; **: p<0.01; ***: p<0.001

Hypothesis 1 posited that information quality (INQ) influences online banking performance (OBP). The hypothesis was supported, $\beta = 0.274$, $t = 5.8961$, $p < 0.001$. This means that the higher the information quality of online banking, the higher its performance.

Hypothesis 2 posited that system quality (SYQ) influences online banking performance (OBP). The hypothesis was supported, $\beta = 0.256$, $t = 4.3018$, $p < 0.001$). This means that the higher the system quality of online banking, the higher its performance.

Hypothesis 3 posited that e-service quality (E-SQ) influences online banking performance (OBP). The hypothesis was supported, $\beta = 0.128$, $t = 3.1208$, $p < 0.001$. This suggests that the higher the e-service quality of online banking, the higher its performance.

The study then estimated other direct relationships between the independent variables (INQ, SYQ, E-SQ) and the dependent variable (continuous-use intention), as posited by hypotheses 4-6 (H4 to H6). Figures 4.8 and 4.9 and Table 4.15 show the path coefficients, *t*-statistics, and *p*-values findings of the model.

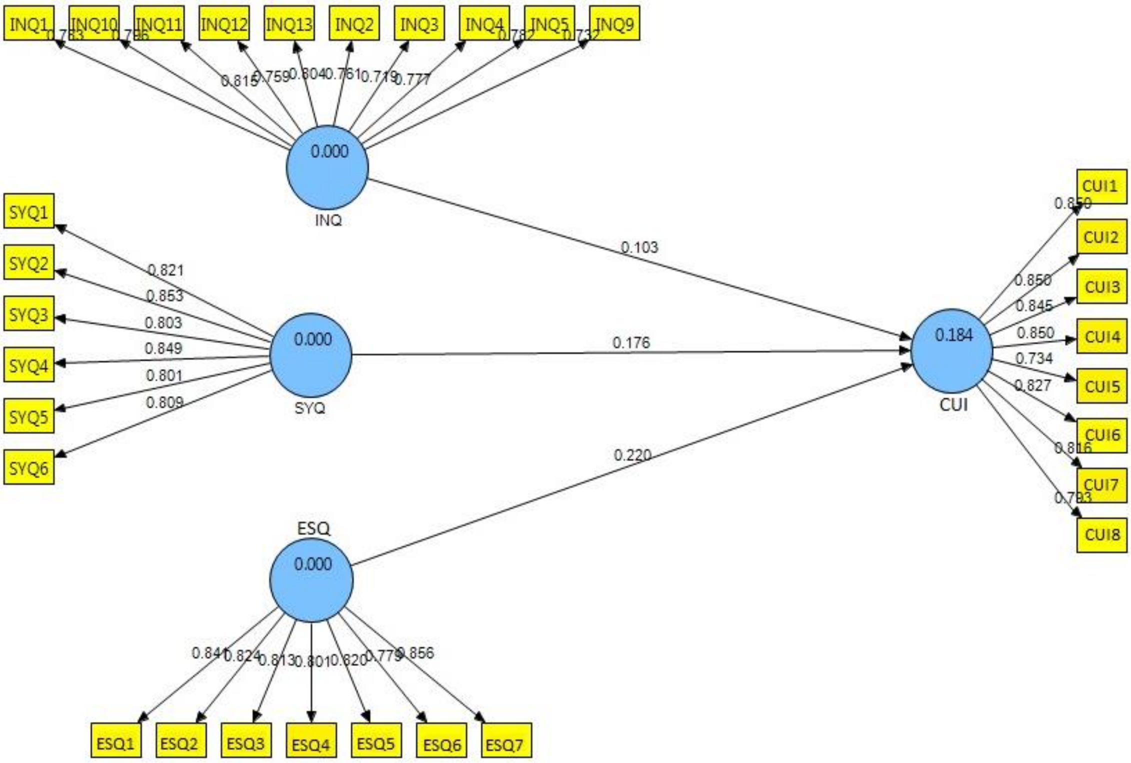

Figure 4.8: PLS Algorithm Direct Relationship (INQ, SYQ, E-SQ, and CUI)

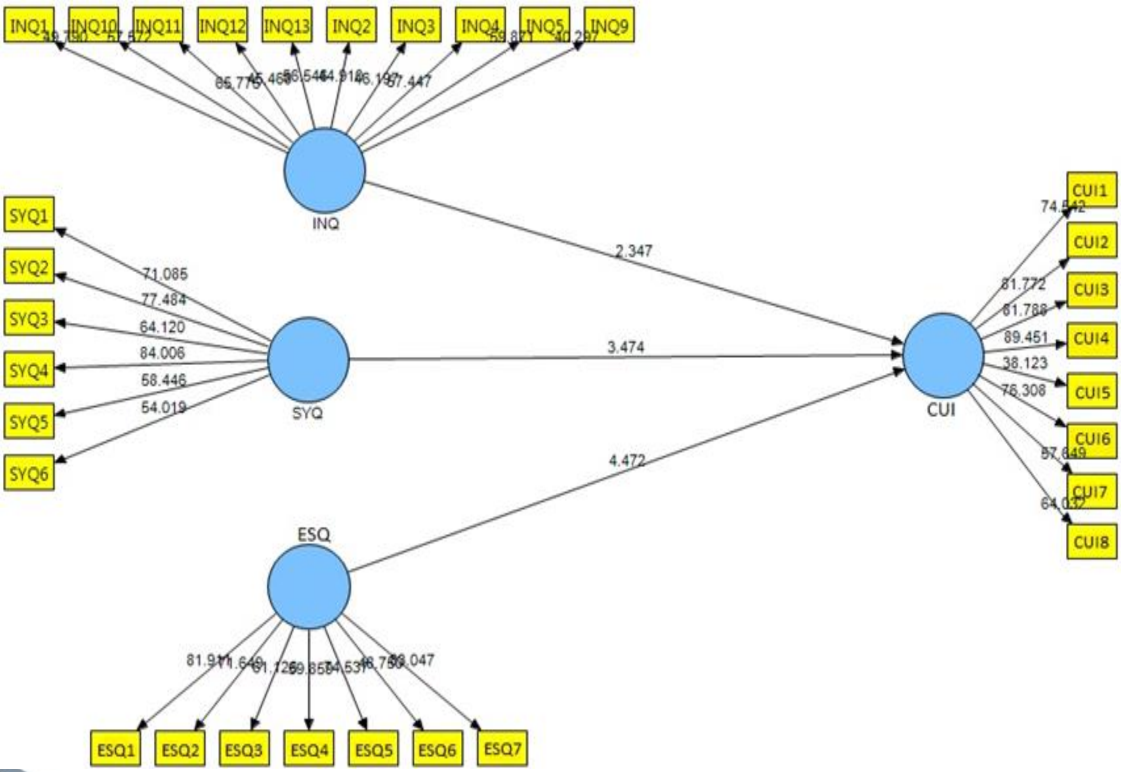

Figure 4.9: PLS-SEM Bootstrapping Direct Relationship(INQ, SYQ, E-SQ, and CUI)

Using PLS-SEM algorithm and bootstrapping, Figure 4.8 presents the path coefficient from the independent variables to the dependent variable. The findings showed that all independent variables had positive path coefficients towards the dependent variable. The bootstrapping finding in Figure 4.9 revealed that the paths from INQ ($p < 0.05$), SYQ ($p < 0.01$), and E-SQ ($p < 0.001$) towards continuous-use intention were significant. The hypotheses were accepted. These results suggest that INQ, SYQ, and E-SQ play a critical role in the continuous-use intention of online banking in Jordan. Table 4.15 shows the path coefficients, *t*-statistics, and *p*-values.

Table 4.15: Direct Relationship (INQ, SYQ, E-SQ, and CUI)

Hypothesis	Path	Path Coefficient	Standard Error	T-Statistics	P-Value	Decision
H4	INQ -> CUI	0.103*	0.044	2.3467	0.020	Supported
H5	SYQ -> CUI	0.176**	0.051	3.4737	0.001	Supported
H6	E-SQ -> CUI	0.220***	0.049	4.4718	0.000	Supported

*: p<0.05; **: p<0.01; ***: p<0.001

Hypothesis 4 posited that information quality (INQ) influences continuous-use intention (CUI) of online banking. The hypothesis was supported, $\beta = 0.103$, $t = 2.3467$, $p < 0.05$. This suggests that the higher the information quality of online banking, the higher the customers' continuous-use intention of online banking.

Hypothesis 5 posited that system quality (SYQ) influences continuous-use intention (CUI) of online banking. The hypothesis was supported, $\beta = 0.176$, $t = 3.4737$, $p < 0.01$. This shows that the higher the system quality of online banking, the higher the customers' continuous-use intention of online banking.

Hypothesis 6 posited that e-service quality (E-SQ) influences continuous-use intention (CUI) of online banking. The hypothesis was supported, $\beta = 0.220$, $t = 4.4718$, $p < 0.001$. This shows that the higher the quality of online banking, the higher the customers' continuous-use intention of online banking.

The last direct relationship was between the mediator (continuous-use intention) and the dependent variable (online banking performance), as posited by hypothesis 7 (H7). Figures 4.10 and 4.11 and Table 4.16 show the path coefficient, *t*-statistics, and *p*-value of the model.

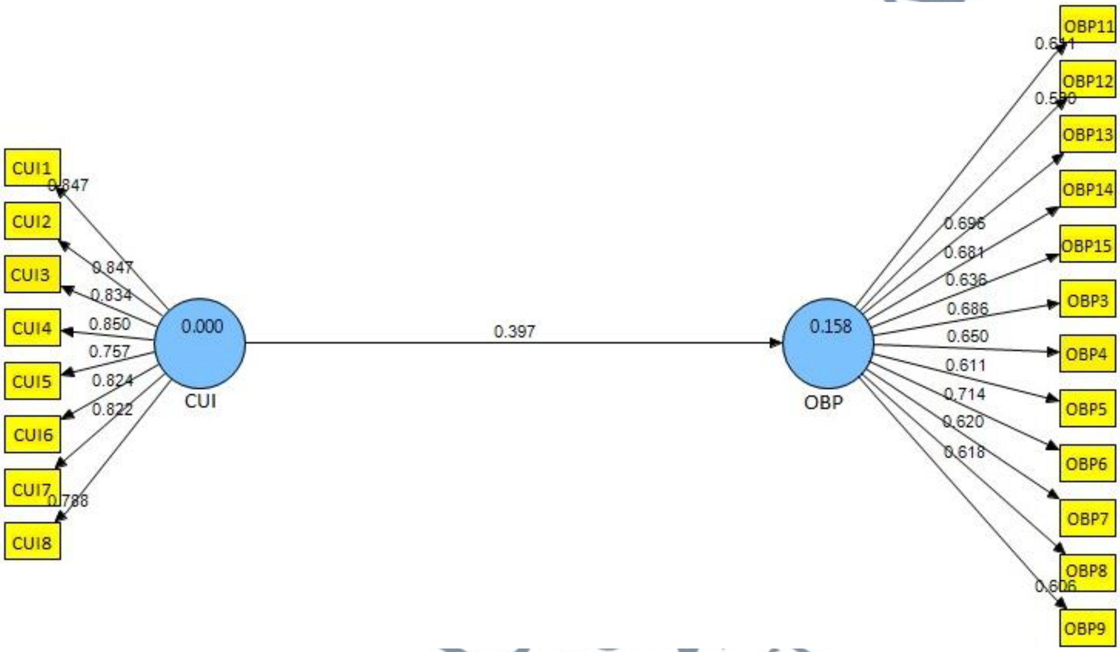

Figure 4.10: PLS Algorithm Direct Relationship (CUI and OBP)

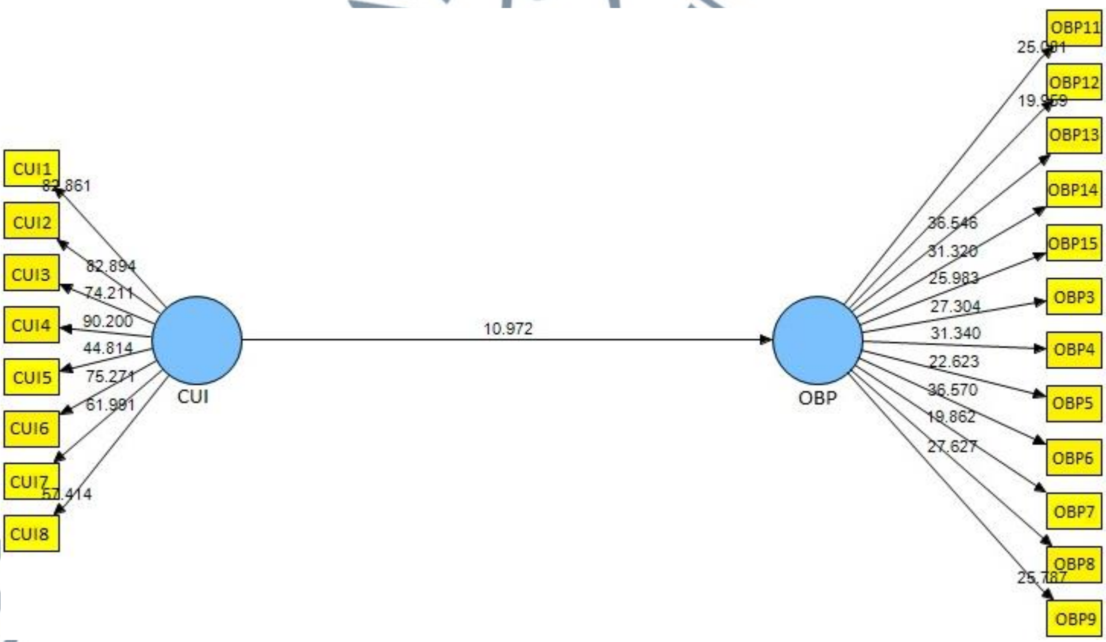

Figure 4.11: PLS-SEM Bootstrapping Direct Relationship (CUI and OBP)

Using PLS-SEM algorithm and bootstrapping, Figure 4.10 reveals the path coefficient from the independent variable to the dependent variable. The finding shows that the independent variable had a positive path coefficient towards the dependent variable. The bootstrapping finding in Figure 4.11 revealed that the relationship between the independent variable (CUI) and the dependent variable (OBP) was significant, $p < 0.001$. Therefore, the hypothesis was accepted. Table 4.16 shows the path coefficient, *t*-statistics, and *p*-value.

Table 4.16: Direct Relationship (CUI and OBP)

Hypothesis	Path	Path Coefficient	Standard Error	T-Statistics	P-Value	Decision
H7	CUI -> OBP	0.397***	0.036	10.9718	0.000	Supported

*: p<0.05; **: p<0.01; ***: p<0.001

Hypothesis 7_0 posited that continuous-use intention (CUI) of online banking influences online banking performance (OBP). The hypothesis was supported, $\beta = 0.397$, $t = 10.9718$, $p < 0.001$. This means that the higher the customers' continuous-use intention of online banking, the higher its performance.

4.8.2.2.2 Indirect Relationships (Mediation Test)

After estimating the direct relationships, the mediation effect of continuous-use intention on the relationships between INQ, SYQ, E-SQ, and online banking performance was estimated. As shown in Figure 4.12, the path coefficients of the three independent variables (INQ, SYQ, and E-SQ) and the mediator (continuous-use intention) towards the dependent variable (online banking performance) were positive. The bootstrapping findings shown in Figure 4.13 indicated that all the relationships were significant.

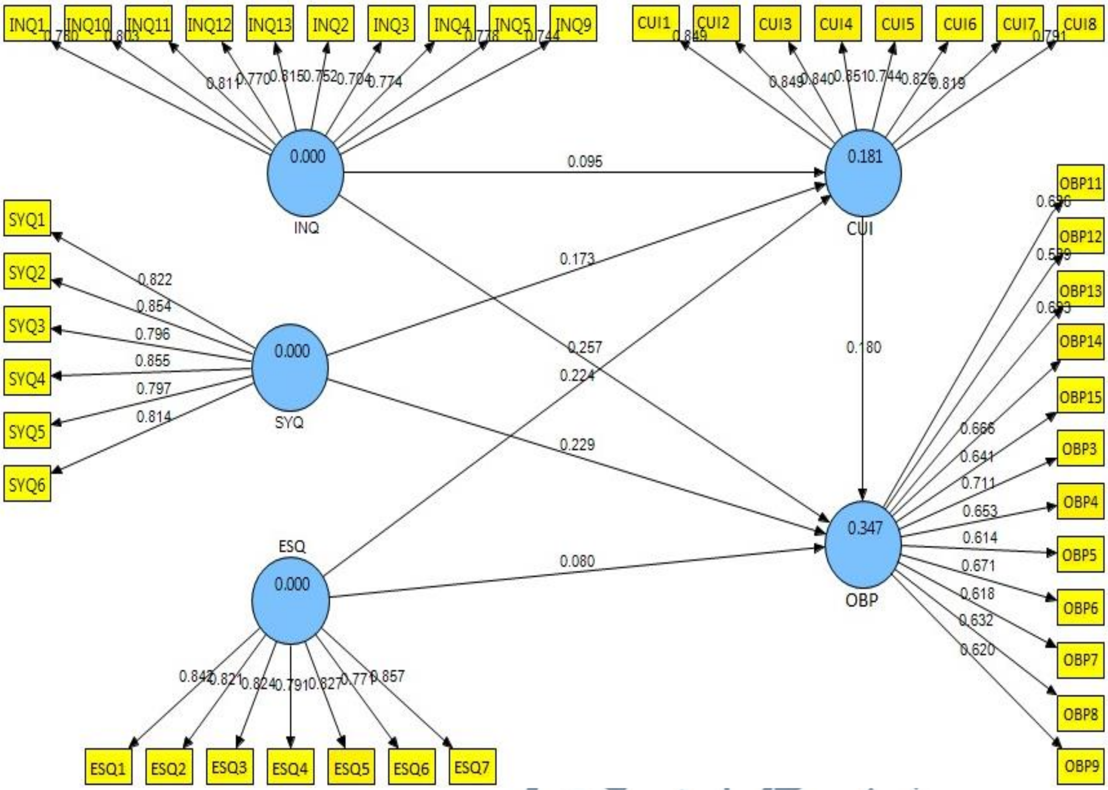

Figure 4.12: PLS Algorithm Indirect Relationship

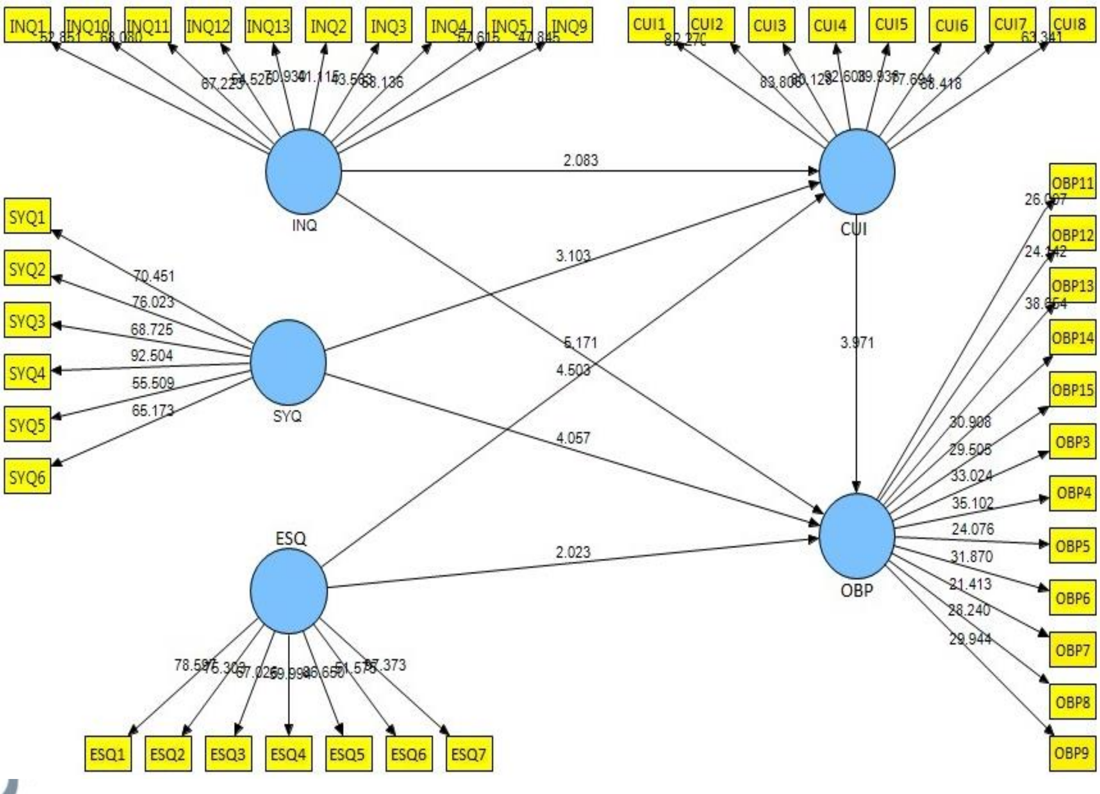

Figure 4.13: PLS-SEM Bootstrapping Indirect Relationship

Mediation analysis estimates the indirect impact of an intervening variable on the relationship between the independent and dependent variables. Preacher & Hayes (2008c) explained that there are several methods to test mediation, one of which is the serial approach or causal steps strategy (Hoyle & Robinson, 2004), which refers to the four steps proposed by Baron & Kenny (1986). Other methods for mediation analysis are the product of coefficients, or Sobel test (Sobel, 1982), product distribution (MacKinnon et al., 2004; MacKinnon et al., 2007), and bootstrapping (Hayes, 2009a; (Hayes & Scharkow, 2013). The most common mediation analysis technique is bootstrapping, since it creates an empirical representation of the sampling distribution of the indirect impact (Hayes, 2009a; Hayes & Scharkow, 2013).

For mediation to hold, the four conditions of Baron & Kenny, (1986) must be met. The first condition is that there must be a total effect ($X \rightarrow Y$) relationship between the independent variables and the dependent variable (c). However, it is not always essential for the total effect to be significant, as a significant indirect effect, and thus mediation, may still exist with a non-significant total effect (Hayes, 2009a; Rucker et al., 2011; MacKinnon et al., 2002; Zhao et al., 2010). The second and third conditions are that the independent variable should significantly influence the mediator (a), that the mediator should in turn significantly influence the dependent variable (b) (Preacher & Hayes, 2008b). If either of the relationships is not significant, the mediator cannot mediate between the independent and dependent variables (Preacher & Hayes, 2008b). Finally, the total direct effect of the independent variables on the dependent variable (c') must be non-significant or smaller than the indirect effect (c). However, Rucker et al. (2011) challenged the emphasis on labelling a mediation as either full or partial following the changing total effect value after the inclusion of a mediator.

The bootstrapping technique starts by assessing the path model of the direct relationship from the independent variables to the dependent variable in the absence of a mediator. These path models contain the path coefficients and *t*-values respectively estimated by the PLS-SEM algorithm and bootstrapping (Hair et al., 2013a). In the second step, the path model is estimated with a mediator, focusing on whether the relationships between the independent variable and mediator, and between the mediator and dependent variable, are significant. It is essential but not sufficient for a mediation effect. Finally, the product of the two significant path coefficients is divided by the standard error of the product $\frac{(axb)}{Sab}$ to test the significance of the indirect effect.

Numerous studies have highlighted the advantages of and justifications for using the bootstrapping technique to examine mediation (Hair et al., 2013a; Hayes, 2012b; Hayes & Preacher, 2010; Preacher & Hayes, 2008b; Zhao et al., 2010). According to Hayes & Preacher (2010), the four steps of Baron & Kenny (1986) cannot include standard errors, while the Sobel test requires the assumption of a normal sampling distribution of the indirect effect. However, the sampling distributions of the effect of the independent variable on the mediator and the effect of the mediator on the dependent variable are asymmetric (Preacher & Hayes, 2007a). The distribution of the product method is a little complicated to use without the support of tables, and it also requires the assumption of a normal sampling distribution (Hayes, 2009a).

Rodriguez-Entrena et al. (2016) maintained that bootstrapping could be used to build a confidence interval and mitigate the aforementioned flaws, as it allows the distribution of an indirect effect to be examined empirically. Moreover, Zhao et al. (2010) argued that the bootstrapping method solves those problems by creating an empirical sampling distribution (*a* x *b*). Hayes & Preacher (2010) and Preacher & Hayes (2008b) explained that the fundamental advantage of the bootstrapping method is that it does not need any assumptions regarding the sampling distributions of the indirect effect or its product. Put another way, the bootstrapped confidence interval can be asymmetric, unlike the regular confidence intervals of other methods. This is because bootstrapping provides an empirical estimation of the sampling distribution of the indirect effect, while other methods assume a normal sampling distribution. Additionally, bootstrapping generates an interval estimate of a population parameter that cannot be achieved by other mediation analyses (Rodriguez-Entrena et al., 2016).

Because of its advantages, Hair et al. (2013a) and Hayes & Preacher (2010) proposed examining the significance of mediation using bootstrapping techniques. Therefore, this research examined the mediating effect of continuous-use intention on the positive effects of INQ, SYQ, and E-SQ on online banking performance by bootstrapping with 372 cases and 1,000 sub-samples. Figure 4.12 illustrates the PLS-SEM algorithm after adding continuous-use intention as the mediator, and Figure 4.13 shows the bootstrapped estimations after adding continuous-use intention as the mediator.

The bootstrapping results were used to multiply paths *a* and *b*, the result of which was divided by the standard error of the product (a x b) to obtain t. Table 4.17 shows the results: CUI mediated the positive relationships between SYQ and OBP ($\beta = 0.035$, $t = 2.492$, $p < 0.001$), E-SQ and OBP ($\beta = 0.046$, $t = 2.718$, $p < 0.01$), but not between INQ and OBP ($\beta = 0.017$, $t = 1.844$, $p > 0.05$). The results of the hypotheses are summarised in Table 4.18.

Table 4.17: Results of Mediation Test

Hypothesis	Path	Path Coefficient	Standard Error	T-Statistics	P-Value	Decision
H8	INQ ->CUI->OBP	0.017	0.019	1.844	0.065	Not Supported
H9	SYQ->CUI->OBP	0.035***	0.03	2.492	0.007	Supported
H10	E-SQ->CUI>OBP	0.046**	0.029	2.718	0.013	Supported

*: p<0.05; **: p<0.01; ***: p<0.001

Table 4.18: Recapitulation of the Hypotheses Findings

Hypotheses	Statement of Hypotheses	Decision
H_1	Quality of information has a positive direct effect on online banking performance	Supported
H_2	Quality of system has a positive direct effect on online banking performance	Supported
H_3	Quality of e-service has a positive direct effect on online banking performance	Supported
H_4	Quality of information has a positive direct effect on customers' continuous-use intention of online banking	Supported
H_5	Quality of system has a positive direct effect on customers' continuous-use intention of online banking	Supported
H_6	Quality of e-service has a positive direct effect on customers' continuous-use intention of online banking	Supported
H_7	Continuous-use intention of online banking has a positive direct effect on online banking performance	Supported
H_8	Continuous-use intention mediates the negative relationship between information quality and online banking performance	Not supported
H_9	Continuous-use intention mediates the positive relationship between system quality and online banking performance	Supported
H_{10}	Continuous-use intention mediates the positive relationship between e-service quality and online banking performance	Supported

Source: Author

4.8.2.3 Evaluation of Effect Size (f^2)

The next test evaluated the effect size (f^2), as proposed by Hair et al. (2013a). Effect size is the change in R^2 when an exogenous construct is included in the model and when it is eliminated from the model. The purpose is to assess whether the omitted exogenous variables have a significant effect on the endogenous variables (Hair et al., 2017c). Effect sizes of 0.02, 0.15, and 0.35 are respectively small, moderate, and large (Cohen, 2013; Henseler & Fassott, 2010). Nonetheless, Chin et al. (2003) stressed that even the smallest f^2 must be considered as it can influence the endogenous variables. Effect size is calculated using the following formula (Cohen, 2013):

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

where;

f^2 = effect size

R^2included = R^2 value of the endogenous variable when all the exogenous variables are included in the model

R^2excluded = R^2 value of the endogenous variable when the defined exogenous variable is excluded from the model

In this research, the effect size of the exogenous variables on the endogenous variables were evaluated and reported. Table 4.19 reveals the effects of each exogenous variable on the endogenous variable. The results showed the effect sizes of the exogenous variables were small to the structural model. These mean that INQ, CUI, E-SQ, and SYQ variables have substantive small influence of effect size toward the model or endogenous variable.

Table 4.19: Effect Size (f^2)

Variables	f^2	**Effect Size**
INQ -> CUI	0.004	Small
INQ -> OBP	0.064	Small
CUI -> OBP	0.051	Small
E-SQ -> CUI	0.036	Small
E-SQ -> OBP	0.003	Small
SYQ -> CUI	0.018	Small
SYQ -> OBP	0.049	Small

Note: INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality

4.8.2.4 Evaluation of Predictive Relevance (Q^2)

Another evaluation of the structural model is the model's predictive relevance. It can be evaluated using the Stone–Geisser criterion, which supposes that the model must be able to predict the indicators of the endogenous latent variable (Henseler et al., 2009). Q^2 can be estimated using Stone-Geisser's Q^2 test, which can be measured using blindfolding procedures (Henseler et al., 2009; Hair et al., 2019). Therefore, this research used the Stone-Geisser test to obtain the cross-validated redundancy for the endogenous variable (Hair et al., 2019). Table 4.20 presents the cross-validated redundancy for continuous-use intention and online banking performance.

Table 4.20: Predictive Relevance (Q^2)

Total	**SSO**	**SSE**	**Q^2 = 1-SSE/SSO**
CUI	2976	2625.49	0.118
OBP	4464	3857.65	0.136

Note: CUI: Continuous-use Intention; OBP: Online Banking Performance

Table 4.20 shows that all Q^2 values were higher than zero for both continuous-use intention (0.118) and online banking performance (0.136), indicating the predictive relevance of the model. These results are consistent with the criteria proposed by Hair et al. (2019) and Henseler et al. (2009), that a Q^2 value above zero indicates that the model has predictive relevance, while a value of less than zero indicates otherwise.

4.8.2.5 Evaluation of Goodness-of-Fit Index (GoF)

Tenenhaus et al. (2004) defined GoF as the global goodness-of-fit. It is the geometric mean of both average variances extracted (AVE) and the average R^2 of the endogenous variables. The purpose of GoF is to evaluate overall model fit, not only at the measurement or structural level (Chin, 2010; Henseler & Sarstedt, 2013). GoF index can be classified into 3 criteria which are small, medium, and large validating power for the values 0.10, 0.25, and 0.36 respectively (Wetzels et al., 2009). Consequently, the formula for GoF index of a model is as follows (Wetzels et al., 2009):

$$GOF = \sqrt{\overline{AVE} \times \overline{R^2}}$$

where;

GoF = goodness-of-Fit

AVE = average communality

R^2 = coefficient of determination

Table 4.21: Goodness of Fit (GoF)

Variables	**AVE**	**R Square**
INQ	0.599	
CUI	0.675	0.18
OBP	0.416	0.35
E-SQ	0.671	
SYQ	0.678	
Average	**0.608**	**0.265**
GoF		**0.401**

Small: GoF = 0.10; Medium: GoF = 0.25; Large: GoF = 0.36
Note: INQ: Information Quality; CUI: Continuous-Use Intention; OBP: Online Banking Performance; E-SQ: E-Service Quality; SYQ: System Quality

Table 4.21 indicates, the average of AVE is 0.608 for endogenous variables and the average R^2 is 0.265 for all dependent variables.

Thus;

$$GOF = \sqrt{0.608 \times 0.265} = 0.401$$

With this calculated score of GoF, it exceeds the cut-off value of 0.25 and this indicates the proposed model performed better than the baseline model.

4.9 Conclusions

This chapter has presented the analysis of data collected with questionnaires distributed in commercial banks in north, central, and south Amman. The chapter has described the response rate, sample characteristics, and non-response bias test. It has also shown how the data were initially examined and screened, including an assessment of outliers, missing value, normality, and multicollinearity. Next, the measurement and structural models using PLS-SEM were evaluated, also included the findings of the hypotheses testing.