CHAPTER 4

DATA ANALYSIS AND FINDINGS

4.1 Introduction

This chapter presents the data analysis and research findings based on the data collected from the sampled MSMEs owner-managers in North-West Nigeria. The main goal of this empirical survey study was to investigate the noneconomic factors that influence general takaful adoption among MSMEs owner-managers in North-West Nigeria, as well as examine the moderating role of religiosity on the relationship between the predictor variables and general takaful adoption. First, the chapter explains the response rate, data preparation and screening followed by the descriptive statistics of the respondents' demographic profiles. Second, the chapter presents the descriptive statistics of latent constructs used in the study. Third, the chapter discusses the assessment of the measurement (outer) and structural (inner) model using PLS-SEM technique. The measurement model was evaluated to establish convergent validity, discriminant validity and internal consistency reliability. The structural model was also assessed to check the significance of the path coefficients, the variance explained in the endogenous construct (R^2), effect size (F^2), predictive relevance of the model (Q^2) and out-of-sample predictive relevance (PLSpredict). Fourth, the results of the moderating effects of religiosity on the research model was presented. Fifth, the summary of hypotheses testing was reported. Finally, the chapter summary was presented.

4.2 Test of Non-Response Bias

Non-response (late-response) bias is a situation in which non-respondents (or late responders) from a given sample differ systematically from respondents in the same sample (i.e., early responders) (Prince, 2012). Non-response bias is a common challenge encountered in survey studies (Sedgwick, 2014; Armstrong & Overton, 1977). Moreover, non-response bias can threaten the external validity (generalizability) of research outcomes. However, ensuring a high response rate can reduce non-response bias (Sedgwick, 2014). Also, another way of estimating non-response bias is through extrapolation. Extrapolation techniques are used to infer the unknown (non-respondents) from the known (late responders) and are based on the presumption that respondents who respond late are like non-respondents (Armstrong & Overton, 1977).

A common extrapolation method used by researchers to estimate non-response bias is by comparing the group mean and standard deviation of the two groups (i.e., early and late respondents) (Sheikh & Mattingly, 1981; Armstrong & Overton, 1977**).** In this study, respondents were categorised into two independent groups: early responders and late responders based on their response time to the questionnaires concerning 9 latent constructs in the research model (relative advantage, compatibility, complexity, uncertainty, awareness, social influence, government support, religiosity, and general takaful adoption) (see Table 4.1). Non-response bias is not an issue if the group mean and standard deviation of the two groups do not vary significantly. Additionally, Levene's Test for Equality of Variances (i.e., independent sample t-test results) as shown in Table 4.1 further confirms the null hypothesis (i.e., there is no significant difference between the two groups) Thus, non-response bias was not a threat in this study.

Table 4.1: Non-Response Bias Test

		Group Statistics				Levene's Test for Equality of Variances	
Var	**Resp.Time**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**F**	**Sig.**
CP	Early Response	213	5.2962	1.6921	.11594		
	Late Response	82	5.3964	1.6669	.18408	.002	.963
CX	Early Response	213	3.8327	1.8811	.12889		
	Late Response	82	3.3793	1.8576	.20514	.071	.789
UC	Early Response	213	3.3189	1.9233	.13178		
	Late Response	82	2.9512	1.9932	.220113	.054	.817
AW	Early Response	213	4.2030	1.9321	.13238		
	Late Response	82	4.2073	2.0106	.22204	.541	.463
SI	Early Response	213	4.6580	2.0084	.13761		
	Late Response	82	4.7303	1.9932	.22012	.334	.564
GS	Early Response	213	3.9888	1.9273	.13205		
	Late Response	82	3.9863	2.1007	.23199	1.707	.192
RA	Early Response	213	5.0976	1.7304	.1185		
	Late Response	82	5.3022	1.7511	.1933	.001	.980
RG	Early Response	213	5.48	1.731	.119		
	Late Response	82	5.68	1.640	.181	.663	.416
AI	Early Response	213	5.2747	1.8616	.12756		
	Late Response	82	5.5984	1.7872	.19736	.354	.552

4.3 Response Rate

A total of 400 survey questionnaires were administered to MSMEs owner-managers and 347 (86.8%) were returned. Out of the 347 questionnaires collected, 45 (11.3%) respondents did not meet the study scope inclusion criteria (i.e., only Muslim MSME owner-manager and number of employees within 1-50) and thus were excluded. Furthermore, additional 7 (1.7%) questionnaires were deemed invalid due to large percentage of missing values. Hence, 295 returned questionnaires were considered valid for subsequent analysis in the study. Overall, a response rate of 73.8% was achieved (Table 4.1). Comparable with similar and related studies in the literature, the response rate was considered adequate and within the range of previous samples (Salleh et al., 2021; Dandago et al., 2020; Musah et al., 2020). For instance, Dandago et al. (2020) conducted a survey on takaful patronage among entrepreneurs in Kano (North-West, Nigeria) and achieved a 70.5% response rate. Likewise, Salleh et al. (2021) conducted a study on SMEs demand for general takaful in Malaysia and achieved a response rate of 69.5%. Furthermore, following the guidelines suggested by previous scholars (Sekaran & Bougie, 2016; Kline, 2015; Hair et al., 2014) the response rate in this study was satisfactory. Additionally, 240 questionnaires were distributed in Kano and 160 in Kaduna (total of 400) respectively. A total of 206 questionnaires were returned in Kano of which 21 were first discarded due to scope inclusion criteria. Furthermore, additional 4 were discarded due to incomplete responses reducing the number to 181 valid responses. Similarly, 141 questionnaires were returned in Kaduna and 24 were excluded for not meeting study scope inclusion criteria. Also, another 3 were considered invalid due to incomplete responses reducing the total number of valid responses to 114. Table 4.3 presents the breakdown of the respondents by state.

Table 4.2: Questionnaires Response Rate

Response	Frequency rate
Number of questionnaires distributed	400
Returned questionnaires	347
Excluded due to unfulfilled criteria	45
Returned and excluded questionnaires	7
Returned and usable questionnaires	295
Questionnaires not returned	53
Overall response rate	86.8%
Valid response rate	73.8%

Table 4.3: Respondents by State

S/N	Location of Respondent	Number	Frequency (%)
1	Kano	181	61.4%
2	Kaduna	114	38.6%
	Total	**295**	**100%**

4.4 Common Method Bias Test

One way of ensuring the quality, validity and reliability of study outcomes is by applying rigorous methods when undertaking research. One of the most common factors that hinders rigour, especially in behavioural research is common method bias (CMB) (also known as common method variance [CMV]) (Jordan & Troth, 2020; Podsakoff, MacKenzie & Podsakoff, 2012; Podsakoff, MacKenzie, Lee & Podsakoff, 2003). CMB is more common in survey studies that use self-reported data (i.e., such as in survey questionnaires) and in which the research data are collected using the same method which can result in the "artificial inflation of relationships" (Jordan & Troth, 2020). Among the major potential causes of CMB include social desirability, consistency motif, transient mood, item ambiguity, scale length, common scale anchors, item characteristic effects, acquiescence biases (yea-saying and nay-saying) among others (Podsakoff et al., 2003).

Since this study used self-reported data from MSMEs owner-managers in Northwest Nigeria, the need then arises to apply remedies suggested in the literature to diminish the effect of CMB. Two techniques have been suggested in the literature to minimize the effect of CMB in research studies (Jordan & Troth, 2020; Podsakoff et al., 2003). The first approach is by applying procedural remedies which should be embedded in the study design. Example of some procedural remedies include ensuring respondents anonymity and confidentiality, reducing evaluation apprehension, reducing item ambiguity among others. The second approach is by applying statistical remedies such as the Harman's single-factor test. Consequently, in this study both procedural and statistical remedies were employed.

First, the research instrument was subjected to expert review to ascertain the clarity, appropriateness and content validity of the questionnaire (see Chapter 3). Furthermore, a covering letter was attached with the questionnaire assuring the anonymity and privacy of the respondents, as well as informing them that there are no right or wrong responses and that they should endeavour to answer the questions to the best of their knowledge (see Appendix 2). These applied remedies can diminish respondents' evaluation apprehension and reduce the_influence of socially desirability bias, acquiescence biases, and consistency motif with how they presume the researcher wants them to respond to the questionnaire (Podsakoff et al., 2003).

Second, the Harman's single-factor test was calculated in SPSS (un-rotated factor analysis with fifty-six items of all latent constructs). The results of the test revealed that no single factor accounted for more than 50% of the variance. Furthermore, only 28.236% of the total variance (Table 4.4) was accounted by a single factor which is below the threshold of 50% (Podsakoff & Organ 1986), suggesting that common method bias was not a threat in this study.

Table 4.4: Results of the Harman's Single Factor Test

Initial Eigenvalues				Extraction Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	15.812	28.236	28.236	15.812	28.236	28.236

4.5 Data Screening

Data Screening is an essential aspect of data analysis which if skipped could jeopardize the entire outcome of the analysis. Hence, researchers are advised to spend some time in screening their data for possible errors (Pallant, 2016). Data screening ensures the cleanliness and accuracy of collected data. Data screening entails checking for missing values, outliers, normality and multicollinearity. The main objective for data screening is to ensure the accuracy and reliability of data analysis results and to confirm that the assumptions of multivariate analysis technique has been fulfilled (Hair et al., 2014; Kline, 2005). Hence, the data screening process are discussed in the following subsections.

4.5.1 Assessment of Missing Values

After collecting the data, the next step was to code and input the data into the SPSS (IBM SPSS version 23). The latent constructs items were coded with two letters and a numerical identifier attached (e.g., RA1, CP1, CX5 etc.). The options in the demographic section (A) as well as the Likert scale options in sections B and C were all entered in numerical form. For instance, gender was coded as 1 for male and 2 for female. The next stage of the data screening process was to check for missing values. Missing values are a common phenomenon in survey studies utilising questionnaires. Cohen & Cohen (1983) suggested that missing values of 10% and below may not affect the results of a study. However, for extreme cases of missing values (25% and above), Tabachnick & Fidell (2013), Sekaran & Bougie (2016) advised that the cases should be removed from the analysis.

After cross-checking through manual as well as descriptive statistics, no extreme cases of missing data were found and thus all 295 cases were left for further analysis. Furthermore, descriptive statistics was run again to check for missing values within acceptable range (i.e., <10%). Out of 16,520 data points, 234 were randomly missing, which accounted for 1.42% of the total. Missing values of 5% or less are inconsequential (Tabachnick & Fidell, 2013). Particularly, relative advantage had 25 missing values, compatibility had 22, complexity had 16 missing values, uncertainty had 11, awareness had 18, social influence had 74 missing values, government support 18, religiosity had 14, and adoption intention had 36 missing values each. Hair et al. (2014) suggested that mean replacement can be applied for missing values below 5% per item. From the descriptive statistics of the missing values none of the items had missing values above 5%. Consequently, the mean replacement was applied for missing values in this study. Table 4.5 below shows the statistics of missing values in the study.

Table 4.5: Total and Percentage of Missing Values

Constructs	Number of Missing Values
Relative Advantage	25
Compatibility	22
Complexity	16
Uncertainty	11
Awareness	18
Social Influence	74
Government Support	18
Religiosity	14
Adoption Intention	36
Total percentage	**234/6,520 x 100 = 1.42%**

Note: Percentage of missing values is arrived at by dividing the total number of missing values for the entire data set by total number of data points multiplied by 100.

4.5.2 Assessment of Outliers

Outliers are common occurrences encountered by researchers especially in studies with large samples. An outlier is an observation having extreme value on one variable (a univariate outlier) or a sequence of extreme values on two or more variables (multivariate outlier) which adversely affect statistical analysis and subsequent results (Tabachnick & Fidell 2013). Outliers in a data are observations that do not correspond with the rest of the dataset (Barnett & Lewis, 1994). Multivariate analysis such as PLS-SEM requires that outliers be handled before main research analysis are conducted. Failure to treat outliers (especially extreme outliers) can significantly distort research findings (Hair et al., 2014; Tabachnick & Fidell 2013). In this study, multivariate outliers were checked and treated based on the recommendation of Tabachnick and Fidell (2013). The Mahalanobis (D2) distance test was calculated in SPSS to detect and handle multivariate outliers. To detect outliers, the Mahalanobis distance (D2) values were compared to the critical chi-square value and the number of independent variables (i.e., 9) were set as the degree of freedom. A D2 value greater than the critical chi-square value points to an outlier in the dataset. After comparing the D2 values with the critical value, 6 observations were detected as outliers. The critical chi-square value in this study was 27.88 (Table 4.6). However, the 6 observations detected exceeded the critical value with the maximum D2 having a value of 34.761. To ascertain the level of influence of the outliers on statiscal results, Cook's distance was calculated in SPSS. Following the recommendation of Tabachnick & Fidell (2013), cases having values above 1 should be removed while those with lower values should be retained. After examining the maximum value for Cook's distance, the maximum value was 0.042 (Table 4.7). Consequently, the outliers were retained for further analysis.

Table 4.6: Critical Values for Evaluating Mahalanobis Distance

No. of independent variables (df)	Critical value of $\chi 2$
1	10.83
2	13.82
3	16.27
4	18.47
5	20.52
6	22.46
7	24.32
8	26.13
9	27.88

Source: Tabachnick & Fidell (2007)

Table 4.7: Multivariate outliers and Cook's Distance Test Results

Case	D2	Cook's Distance
91	34.761	0.042
266	34.737	0.013
202	32.954	0.009
7	32.271	0.036
3	31.325	0.006
19	30.331	0.021

4.5.3 Assessment of Normality

Normality of data distribution is an essential component of the assumption of multivariate analysis (Hair et al. 2014). Normality refers to the symmetry, bell-shaped curve distribution having most of the data scores concentrated in the middle leaving smaller frequency scores at the two tail ends of the distribution (Pallant, 2016). Although PLS-SEM as a non-parametric data analysis technique is lax on the normality assumption of data distribution (Astrachan, Patel & Wanzenried, 2014; Hair et al., 2012), it is however highly recommended to examine extreme deviations from normality (Hair et al., 2021). Extreme case of non-normal data can adversely distort statistical tests results and hence pose a threat to the reliability and validity of research outcomes (Hair et al., 2014). The assumption of normality can be assessed through either statistical or graphical procedures (Tabachnick & Fidell, 2013). Though, the use of graphs is recommended for large sample size (i.e., above 200) instead of statistical methods (Tabachnick & Fidell, 2013). However, Hair et al. (2014) suggested that both statistical tests and graphical plots should be applied to assess normality assumption. Consequently, following the recommendation of Hair et al. (2014), both statistical techniques (skewness & Kurtosis test) and graphical methods (histogram & normal probability plot) were employed in this study to evaluate the normality of data distribution.

Skewness refers to the symmetry of the data distribution, while kurtosis refers to the peakedness of the data distribution. Non-normal data are either positively skewed to the right or negatively skewed to the left. As for kurtosis, positive kurtosis signifies a highly peaked distribution, while a negative kurtosis denotes a shorter and flatter distribution. Normal data distribution has skewness and kurtosis of zero or near zero (Tabachnick & Fidell 2013). The recommended threshold for evaluating skewness and kurtosis deviation from normality have been given by scholars (Kline, 2016; Brown, 2015). According to Kline (2016) the absolute values should be between ≤ 3 for skewness and ≤ 7 for kurtosis. Furthermore, Brown (2015) suggested that for SEM analysis, the absolute value should be within the range of -3 to +3 for skewness and -10 to +10 for kurtosis. However, other analysis techniques may have more stringent acceptable values for skewness and kurtosis (Brown, 2015). Since this study uses SEM, the guidelines advanced by Kline (2016) and Brown (2015) were followed. The results from Table 4.8 revealed that the absolute values of the skewness and kurtosis of all variables in the study model were within the acceptable threshold of ≤ 3 and ≤ 7 respectively. Also, the graphical plots of histogram and normal probability plot (Figure

4.1 & 4.2 respectively) shows that the data in this study is normally distributed. The histogram shows a near symmetrical bell-shaped curve distribution. Additionally, the normal probability plot showed that the observed residuals (the dotted lines) are close to the normal distribution line (the straight line). Consequently, data normality assumption was achieved in this study.

Table 4.8: Values of Skewness and Kurtosis of Measured Variables

Study Variables	Skewness	Kurtosis
Relative Advantage	-0.684	-0.093
Compatibility	-.870	0.157
Complexity	0.114	-0.631
Uncertainty	0.423	-0.793
Awareness	-0.106	-0.766
Social Influence	-0.302	-0.953
Government Support	0.062	-0.960
Religiosity	-1.128	0.672
Prior Loss Experience	-1.198	-0.569
Adoption Intention	-1.067	0.484

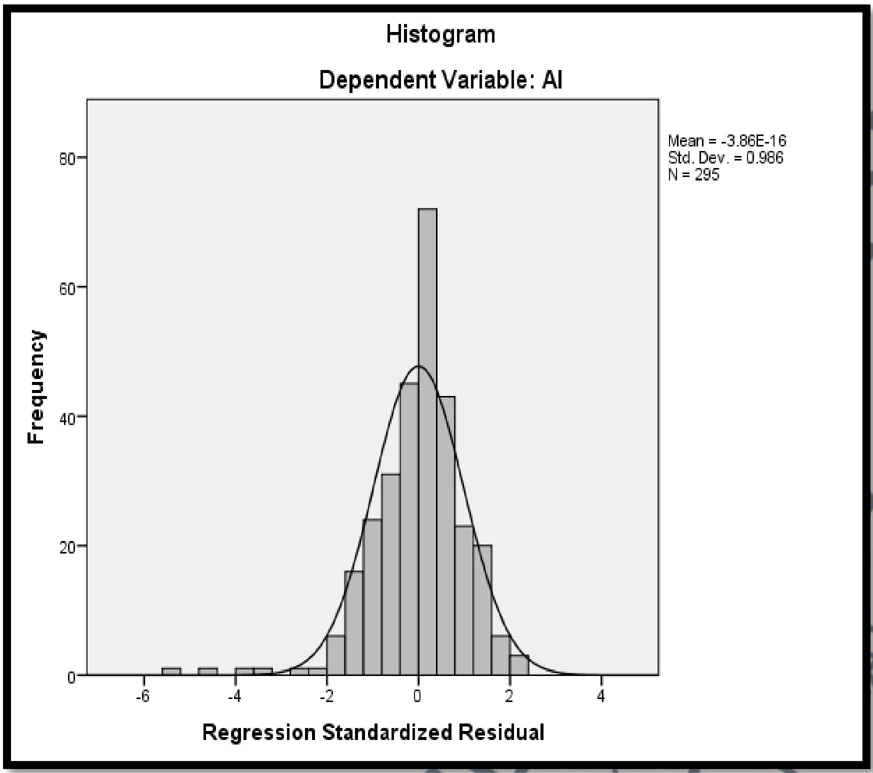

Figure 4.1: Histogram for Test of Normality

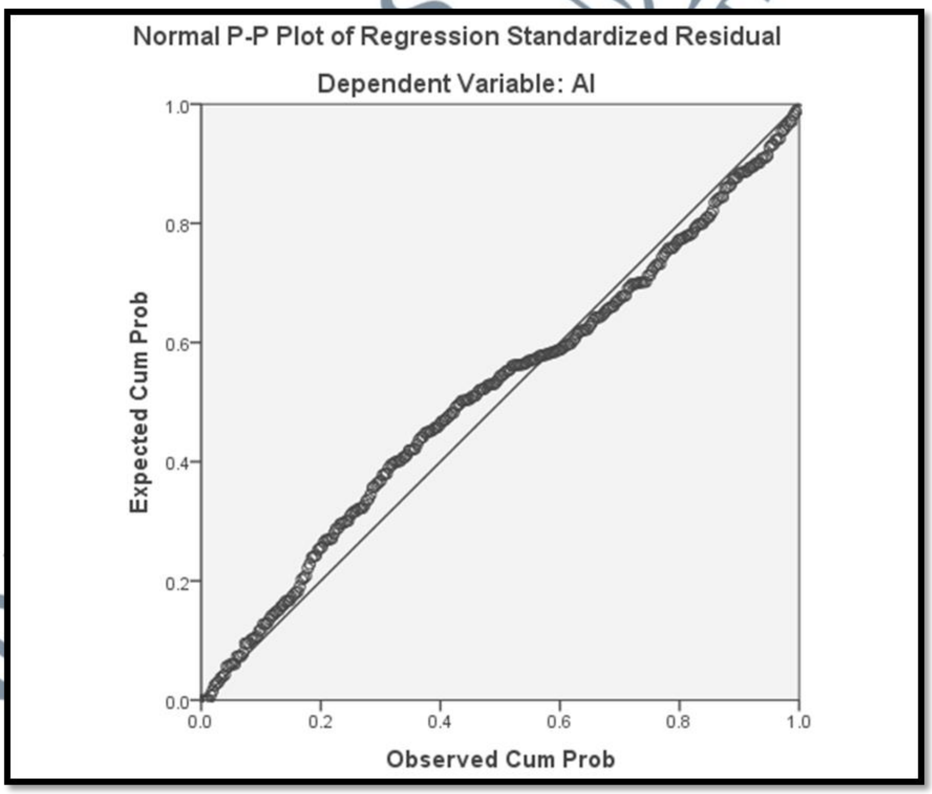

Figure 4.2: Normal Probability Plot

4.5.4 Assessment of Multicollinearity

After assessment of normality, the next multivariate technique assumption to be examined is multicollinearity. Multicollinearity occurs when an independent variable has a high correlation with other independent variables (Hair et al., 2014). This means that the inter-correlation among independent variables is so high that the influence of one predictor variable (reaching 0.90 and above) can be explained by other set of predictors (Pallant, 2016; Tabachnick & Fidell, 2013). The presence of multicollinearity weakens the effect of independent variables on the dependent variable. Furthermore, multicollinearity amplifies the standard errors of coefficients and poses a threat at both logical and statiscal level (Tabachnick & Fidell, 2013).

To assess the presence of multicollinearity, the collinearity diagnostics and correlation matrix were examined. In the collinearity diagnostics table (4.9) the tolerance value (1-squared multiple correlation) column and the variance inflation factor (VIF) column were evaluated. Tolerance values less than 0.20 and VIF value greater than 5 are indicative of the presence of multicollinearity (Hair, et al., 2011). The outcome of collinearity diagnostics tests shows that the tolerance values for all endogenous constructs fall between 0.450 to 0.977, which are all above the given value of 0.20 (Hair et al., 2011). Additionally, the VIF values were within the range of 1.498 to 2.222 below the cut-off value of 5 (Hair et al., 2011). Hence, multicollinearity issues were absent in the endogenous constructs.

Furthermore, the correlation matrix table (Table 4.10) for all endogenous constructs was examined to check for multicollinearity. A high correlation coefficient of 0.90 and above denotes multicollinearity issues between predictor constructs (Tabachnick & Fidell, 2013). The results of correlations show that all predictor constructs were below the limit of 0.90, ranging between ± 0.003 to 0.437, indicating the independence of predictor constructs. Thus, multicollinearity was not an issue in this study.

Table 4.9: Tolerance and Variance Inflation Factors (VIF)

Model		Collinearity Statistics	
		Tolerance	VIF
	(Constant)		
	RA	.468	2.136
	CP	.450*	2.222*
	CX	.668	1.498*
1	UC	.651	1.537
	AW	.640	1.561
	SI	.569	1.758
	GS	.594	1.682
	RG	.483	2.069
	L/E	.977*	1.023

Table 4.10: Correlation Matrix of Endogenous Variables

	L/E	GS	UC	RG	AW	CX	SI	RA	CP
L/E	**1**								
GS	-.003	**1**							
UC	.093	.154	**1**						
RG	-.068	.029	.060	**1**					
AW	.060	.198	-.005	.005	**1**				
CX	-.111	.065	-.511	-.021	-.040	**1**			
SI	.052	.347	.050	-.153	-.364	-.064	**1**		
RA	-.021	.135	-.094	-.292	-.070	.151	-.042	**1**	
CP	-.011	.002	.207	-.437**	-.105	-.086	.053	-.376	**1**

4.6 Profile of Respondents

This section presents the demographic characteristics of the sampled respondents who participated in the study. The following characteristics in terms of frequency distribution and percentages were analysed through SPSS and further described: designation in company, age, gender, education level, type of company, religion, marital status, number of years in operation, number of employees, line of business, location, awareness of takaful, patronage of takaful products, prior loss experience, and perception of takaful support to MSMEs.

4.6.1 Position of Respondents

The designation of sampled respondents was captured in the demographic profile. The designations were categorized into 5 to represent the owner-manager (i.e., owner, director, senior manager, manager & others). As anticipated, the descriptive statistics shows that most of the respondents were owner-managers (207 [owner=120, manager =87]) constituting more than 70% of the total sample. The other three categories constitute less than 30% (Director = 14.6%, senior manager =11.9%, others = 3.4%, respectively) of the total sample size. This shows that most of the MSMEs were directly managed by the owner-managers. This is reflective of the overall characteristics of MSMEs in the country which are mostly micro and managed by the owners directly (SMEDAN & NBS, 2017).

4.6.2 Age of Respondents

The age group of sampled respondents was also captured in the demographic profile. The age groups were classified into 4, representing the young and the old. The first two age groups (18-29 & 30-40) represented the young, whereas the third and fourth age group (41-50 & above 50) represented the old. From the table below (Table 4.11) it is seen that the young age group dominate in the sampled MSMEs owner-managers. Specifically, the 30-40 age group (50.8%) and 18-29 age group (25.8%) constitute 76.6% of the total sample. The other two age groups (41-50 & above 50) constitute only 23.4%. The dominance of the 30-40 age group closely reflects the findings of SMEDAN & NBS (2017). Furthermore, this trend is not surprising because of the high youth unemployment rate (42.5%) in the country (NBS, n.d.). The youths have resorted to engage in business activities to earn their living. Also, another plausible reason for the low percentage of the old age group might be linked to who answered the questionnaire in the company. Most elderly persons prefer to assign responsibilities to their subordinates who are mostly young.

Table 4.11: Age Group of Respondents

Age Group	Frequency	Percentage (%)
18-29	76	25.8
30-40	150	50.8
41-50	53	18.0
Above 50	16	5.4

4.6.3 Gender of Respondents

Table 4.12 shows the gender of respondents in the sample. The results show that the male gender has the major percentage (83.7%). This trend is plausible due to the cultural and religious norms of the North-West region of the country. The female role is mostly within the confines of her home, away from public eyes, whereas the male role is usually outside the home in the public domain. As most business activities require outside activities, the female gender is less engaged in formal business ventures. However, the females are highly engaged in informal business activities that are not easy to reach in terms of data collection.

Table 4.12: Gender of Respondents

Gender	Frequency	Percentage (%)
Male	247	83.7
Female	48	16.3

4.6.4 Education Level of Respondents

The education level of the MSME owner-managers in the sample was captured in the demographic characteristics section. Table 4.13 shows the education level of respondents in the sample. The results show that most of the sampled respondents are relatively educated. Those with degree certificate accounted for 35.3% of the whole sample followed by those with diploma (27.5%). This is an important trend that has links with the rate of youth unemployment (42.5%) (NBS, n.d.) in the country. To be able to survive and provide for their needs, unemployed graduates have resorted to business activities.

Table 4.13: Education Level of Respondents

Education Level	Frequency	Percentage (%)
Primary School	12	4.1
Junior Secondary School	6	2.0
Senior Secondary School	57	19.3
Vocational certificate	11	3.7
Diploma/NCE (Nigeria Certificate in Education)	81	27.5
Degree/HND (Higher National Diploma)	104	35.3
Postgraduate	24	8.1

4.6.5 Type of Company

The Sole Proprietorship and Partnership ownership structure were the most prevalent type of company structure constituting about 80% of the whole sample. Specifically, Sole Proprietorship constitute more than half of the total sampled respondents. The company structure frequency in this study is similar to the findings of SMEDAN & NBS (2017) report which showed that Sole Proprietorship is the major company structure in the MSME sector in Nigeria.

4.6.6 Religion of Respondents

The religion of the respondents was captured in the demographic section. As expected, 100% of the sampled respondents identified with Islam. Based on the research scope and sample selection criteria, other religions were excluded from the analysis. Christianity and other traditional religions constitute an insignificant proportion in the North-West region of Nigeria.

Table 4.14: Religion of Respondents

Religion	Frequency	Percentage (%)
Islam	295	100

4.6.7 Number of Years in Operation

Table 4.15 shows that most of the MSMEs are relatively young in their business life cycle (5-10 years). A sizeable number of MSMEs (46.1%) are within the range of 5-10 years in operation. Additionally, 17.3% are very young in their business life cycle, whereas another 19. 7% (11-15 years) and 16.9% (above 15 years) are fairly matured in their business life cycle.

Table 4.15: Number of Years in Operation

Number of Years in Operation	Frequency	Percentage (%)
0-4 years	51	17.3
5-10 years	136	46.1
11-15 years	58	19.7
Above 15 years	50	16.9

4.6.8 Marital Status of Respondents

Table 4.16 shows that more than half of the respondents are married (63.1%). However, the number of singles is also large (35.6%) which can be linked with the age of the respondents of which majority are relatively young. The percentage of others (which include widow & divorcee) is very low at 1.4% of the total sample.

Table 4.16: Marital Status of Respondents

Marital Status	Frequency	Percentage (%)
Married	186	63.1
Single	105	35.6
Others	4	1.4

4.6.9 Number of Employees

Table 4.17 shows the frequency distribution of number of employees in the sampled MSMEs. From the results it can be observed that 100% (1-10, 11-25 & 26-50) of all MSMEs in the sample have employees within the range of 1-50. Medium sized enterprises were excluded from analysis based on the study scope and sample inclusion criteria. Furthermore, this corresponds with the characteristics of MSMEs in Nigeria. Micro and small enterprises form the bulk of all MSMEs in the country (SMEDAN & NBS, 2017).

Table 4.17: Number of Employees

Number of Employees	Frequency	Percentage (%)
1-10 employees	161	54.6
11-25 employees	91	30.8
26-50 employees	43	14.6

4.6.10 Line of Business of MSMEs

The table below (Table 4.18) displays the frequency distribution of MSMEs line of business. The wholesale/retail (21.7%) and agriculture (17.6%) account for the major proportion of MSME business lines in the sample. A similar statistic was reported in the survey report by SMEDAN & NBS (2017). The other business lines include Manufacturing (13.6%), electronics/computer/power (12.5%), food and beverages/accommodation (9.8%), construction (8.8%), machinery (8.1%), transport and storage (5.8%) and others (2%).

Table 4.18: Line of Business of MSMEs

Line of Business	Frequency	Percentage (%)
Transport & storage	17	5.8
Construction	26	8.8
Machinery	24	8.1
Electronics/computer/power	37	12.5
Manufacturing	40	13.6
Food & beverages/accommodation	29	9.8
Agriculture	52	17.6
Wholesale/retail	64	21.7
Others	6	2.0

4.6.11 Location of Business

The MSMEs sampled were spread across 2 states (Kano & Kaduna) in the North-West region of the country and thus included in the demographic section. The proportionate stratified sample was used to assign the number of samples for each state. Below (Table 4.19) is the frequency distribution of MSMEs according to location. The results show that 61.4% of the respondents are from Kano and 38.6% from Kaduna.

Table 4.19: Location of Business

Location of Business	Frequency	Percentage (%)
Kano	181	61.4
Kaduna	114	38.6

4.6.12 Takaful Awareness

The sampled respondent’s awareness of takaful was also asked in the demographic section. The table below (Table 4.20) shows the frequency distribution of takaful awareness among owner-managers. The responses reveal that there is a moderate awareness of takaful products for MSMEs among the sampled respondents.

More than half of the sample were aware of takaful (50.8%), whereas the other half were not aware of takaful (49.2%). This finding suggests that more awareness campaign and promotional activities are required from takaful operators and other stakeholders such as takaful regulators.

Table 4.20: Takaful Awareness

Takaful Awareness	Frequency	Percentage (%)
Yes	150	50.8
No	145	49.2

4.6.13 Takaful Product Usage

The sampled respondents were also asked about their usage of takaful products for their business risk management. The results from Table 4.21 shows that more than 70% of the sampled MSMEs (70.5%) are not using any general takaful product. This finding reflects the general trend in the insurance industry (SMEDAN & NBS, 2017). As was stated in the problem statement, most MSMEs are yet to adopt general takaful as a risk mitigation strategy even though most of them have suffered loss in their business undertakings. Some plausible reasons hindering the use of takaful by MSMEs maybe the lack of understanding and knowledge of the benefits and compatibility of takaful products to their business ventures.

Table 4.21: Takaful Product Usage

Takaful Product Usage	Frequency	Percentage (%)
Fire & Special Peril Takaful	23	7.8
Burglary & Theft Takaful	9	3.1
Marine Cargo Takaful	5	1.7
Agricultural Takaful	26	8.8
Motor takaful	7	2.4
Goods in Transit Takaful	7	2.4
Group Personal Accident Takaful	10	3.4
None	208	70.5

4.6.14 Past Business Loss Experience

The respondents were further asked whether they have any prior loss experience in their business. This question was asked to measure the influence of past loss experience on takaful adoption intention. It is logically presumed that those that have suffered business loss in the past will be more willing to participate in takaful schemes as a risk protection strategy. The results from Table 4.22 shows that more than 75% of the sampled MSMEs (76.3%) have experienced business loss. This finding supports the past study of Dandago et al. (2020) which highlighted the vulnerability and risk exposure of entrepreneurs, particularly risk related to fire and other natural hazards. Thus, it is expected that loss experience will influence general takaful adoption.

Table 4.22: Business Loss Experience

Loss Experience	Frequency	Percentage (%)
Yes	225	76.3
No	70	23.7

4.6.15 Perception of Takaful Support to Business

This question was asked to investigate the general perception towards general takaful among the respondents. The results from the frequency distribution table (Table 4.23) shows that majority of the sample have a positive perception towards takaful. Precisely, 82% agree that general takaful can support their business in the event of loss. This finding suggests that takaful operators need to take advantage of the positive perception among MSME owner-managers in North-West Nigeria and increase their market share in the MSME segment.

Table 4.23: Perception of Takaful Support to Business

Perception of Takaful Support	Frequency	Percentage (%)
Yes	242	82.0
No	53	18.0

4.7 Descriptive Statistics of Latent Constructs

This section presents the descriptive statistics of all constructs employed in the study. The mean and standard deviation of all latent constructs were calculated. A seven-point Likert scale was used to measure respondents' degree of agreement/disagreement with the measurement items. The scale range was between 1 (extremely disagree) to 7 (extremely disagree). The mean value for all exogenous latent constructs ranges between 3.22 for uncertainty construct (UC) to 5.50 for religiosity construct (RG). Furthermore, the standard deviation for all endogenous constructs ranges between 1.34 for relative advantage (RA) to 1.62 for social influence (SI) and government support. Precisely, relative advantage has a mean and standard deviation of (M=4.97 SD=1.34). This indicates that the perception of relative advantage is relatively high. For compatibility, the mean and standard deviation were (M=5.28 SD=1.38). This shows that the respondents agree with the compatibility of takaful. The mean and standard deviation for complexity were (M=3.72 SD=1.44). This suggests that the perceived complexity of general takaful is moderate to low among the respondents. The mean and standard deviation for uncertainty construct were (M=3.22 SD=1.58). This is indicative that perceived uncertainty of general takaful among respondents is low. For awareness, the mean and standard deviation were (M=4.4 SD=1.50). This means that respondents agree that awareness has moderate influence on general takaful adoption. The mean and standard deviation for social influence were (M=4.5 SD=1.62). This result indicate that the respondents agree that social influence moderately influence general takaful adoption intention. The descriptive results for government support (M=3.73 SD=1.62) implies that government support has a low influence on general takaful adoption. Furthermore, the mean and standard deviation for religiosity were (M=5.50 SD=1.46). This result suggest that respondents agree that religiosity influences general takaful adoption. Finally, the mean and standard deviation for the endogenous construct (AI) were (M=5.49 SD=1.48) suggesting that the respondents agree general takaful adoption was partly due to the influence of some of the exogenous constructs in the study. Table 4.24 shows the results of the descriptive statistics.

Table 4.24: Descriptive Statistics of Latent Constructs

Constructs	Items	Mean	Std Dev
Relative Advantage	7	4.97	1.34
Compatibility	5	5.28	1.38
Complexity	5	3.72	1.44
Uncertainty	6	3.22	1.58
Awareness	8	4.4	1.50
Social Influence	9	4.5	1.62
Government Support	6	3.73	1.62
Religiosity	6	5.50	1.46
Adoption Intention	4	5.49	1.48

4.8 Evaluation of PLS-SEM Results

After presenting the preliminary analysis and descriptive statistics, the next stage was to evaluate the PLS-SEM results. A two-step approach was applied as suggested by Hair et al., (2019) and Henseler, Ringle and Sinkovics (2009). The first step consists of evaluating the measurement model (outer model) through assessing the following: individual item reliability (indicator loadings), internal consistency reliability, convergent validity and discriminant validity. If the measurement model fulfils the requisite criteria, then the structural model can be evaluated. The second step was to evaluate the structural model (outer model) through examining the following:

significance of path coefficients, the coefficient of determination (R^2 value), the effect size (f^2), the blindfolding-based cross-validated redundancy measure (predictive relevance [Q^2]), the model's out-of-sample predictive power by using the PLSpredict technique (Hair et al., 2019; Shmueli, Ray, Estrada & Chatla, 2016) and the significance of the moderating effect.

4.8.1 Measurement Model Evaluation

To estimate the appropriateness of the measurement model in this study, the following analysis were conducted: individual item reliability test, internal consistency reliability test, convergent validity assessment and discriminant validity test (Hair et al., 2019; Henseler et al., 2009).

4.8.1.1 Individual Items Reliability

The reliability of individual items (reflective constructs) is evaluated by looking at the standardized factor loadings of individual indicators (items). Standardized factor loadings that are above 0.708 are usually recommended, as that implies that more than 50% of the indicator variance is explained by the construct being measured (Hair et al., 2019). However, Hair et al., (2021 p. 77) contended that items with factor loadings between the range of 0.40 and 0.70 can be retained if removal of items will affect content validity. Nevertheless, they advised that items with loadings less than 0.40 should always be deleted. Furthermore, Hair et al. (2021 p. 77) recommended that "…. Indicators with loadings between 0.40 and 0.708 should be considered for removal only when deleting the indicator leads to an increase in the internal consistency reliability or convergent validity above the suggested threshold value".

In the present study, 6 items (AW1=0.669, AW7=0.691, CX2=0.561, RA1=0.662, RA5=0.681, UC1=0.599) were found to be below the recommended threshold of 0.708. However, given that the removal of the indicators with loadings between 0.40 and 0.708 did not increase the composite reliability scores or convergent validity values, the items were retained (Table 4.25). Moreover, some items if deleted (for instance CX2) can adversely affect the content validity of the construct and thus retained. Nevertheless, 2 items (CX1 & CX4) were deleted due to very low loadings (<0.40).

4.8.1.2 Internal Consistency Reliability

The second test was to examine the internal consistency reliability of the measures that make up the construct. Internal consistency reliability indicates the degree to which items measuring the same construct are related with each other (Hair et al., 2021). The two popular techniques commonly used to evaluate internal consistency reliability are Cronbach's alpha and composite reliability (CR). This present study used both Cronbach's alpha and composite reliability coefficient to assess internal consistency reliability of items on each construct (Sarstedt et al., 2017). However, Cronbach's alpha gives lower values compared to composite reliability. Moreover, Cronbach's alpha has less measurement precision because the items are unweighted. Conversely, composite reliability uses weighted items based on the factor loadings of individual indicators and, thus, gives a higher reliability (Hair et al., 2019). Scholars have set a minimum of 0.60 coefficient (for both Cronbach's alpha & composite reliability) as acceptable for exploratory research (Hair et al., 2019: Sekaran & Bougie, 2016). However, coefficient of 0.70 to 0.95 are preferred (Hair et al., 2021; Hair et al., 2019; Sarstedt et al., 2017). In this study, both Cronbach's alpha and composite reliability (CR) coefficients of all latent constructs were within the satisfactory threshold recommended by scholars (see Table 4.25). Thus, internal consistency reliability of constructs items was achieved in this study.

4.8.1.3 Convergent Validity

After assessing the reliability of items, the third step in evaluating the measurement model entails confirmation of convergent validity. Convergent validity refers to the extent measurement items correlate with each other to represent a particular construct (Hair et al., 2019; Hair et al., 2014). To evaluate the convergent validity of indicators in relation to the individual constructs being measured, the average variance extracted (AVE) value was calculated. Average variance extracted (AVE) measure shows the average variance shared between a construct and the indicators measuring it. Average variance extracted (AVE) is calculated by squaring the loading of each individual item measuring a construct and thereafter the mean value is computed (Hair et al., 2019). The minimum standard for AVE should be at least 0.50 or above, which indicates that a construct reflects at a minimum 50% of the variance of the indicators measuring it (Hair et al., 2021; Hair et al., 2019). The results of AVE for this study are shown in Table 4.25. Convergent validity was achieved for all latent constructs as the AVE values were all above the recommended threshold of 0.50. The AVE values in this study ranges between 0.575 to 0.772.

Table 4.25: Loadings, Cronbach's Alpha, Composite Reliability (CR) and AVE

Constructs	Items	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Awareness	**AW1**	0.669	0.887	0.915	**0.575***
	AW2	0.782			
	AW3	0.784			
	AW4	0.750			
	AW5	0.819			
	AW6	0.813			
	AW7	0.691			
	AW8	0.745			
Compatibility	**CP1**	0.849	0.881	0.913	0.679
	CP2	0.875			
	CP3	0.859			
	CP4	0.744			
	CP5	0.786			
Complexity	**CX2**	0.561	0.736	0.818	0.610
	CX3	0.785			
	CX5	0.948			
General Takaful Adoption	**AI1**	0.915	0.864	0.931	**0.772***
	AI2	0.897			
	AI3	0.920			
	AI4	0.775			
Government Support	**GS1**	0.823	0.922	0.939	0.718
	GS2	0.851			
	GS3	0.878			
	GS4	0.885			
	GS5	0.815			
	GS6	0.830			
Relative Advantage	**RA1**	0.662	0.887	0.912	0.601
	RA2	0.722			
	RA3	0.851			
	RA4	0.829			
	RA5	0.681			
	RA6	0.817			
	RA7	0.838			
Religiosity	**RG1**	0.854	0.912	0.932	0.696
	RG2	0.866			
	RG3	0.842			
	RG4	0.825			
	RG5	0.791			
	RG6	0.825			

Table 4.25, continued

Constructs	Items	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Social Influence	**SI1**	0.804	0.936	0.946	0.662
	SI2	0.828			
	SI3	0.801			
	SI4	0.800			
	SI5	0.819			
	SI6	0.874			
	SI7	0.779			
	SI8	0.801			
	SI9	0.813			
Uncertainty	**UC1**	0.599	0.898	0.914	0.642
	UC2	0.816			
	UC3	0.865			
	UC4	0.842			
	UC5	0.820			
	UC6	0.836			

4.8.1.4 Discriminant Validity

Confirmation of discriminant validity is the final step in evaluating the measurement model in PLS-SEM. Discriminant validity is a metric measure that reveals the extent to which a particular "construct is empirically distinct from other constructs in the structural model" (Hair et al., 2021p. 78). This distinction entails two things "how much it correlates with other constructs and how distinctly the indicators represent only this single construct" (Sarstedt et al., 2017 p. 18). The two popular techniques for assessing discriminant validity are through the assessment of cross-loadings (Chin, 1998) and Fornell and Larcker (1981) criterion. In establishing discriminant validity through cross-loadings "the loading of each indicator is expected to be greater than all of its cross-loadings" (Henseler et al., 2009 p. 300). Chin (1998) argues that for discriminant validity to be established each indicator should load highest on the construct it is meant to measure than with other constructs in the structural model. For Fornell and Larcker criterion, discriminant validity is established if the square root of a construct's AVE is greater than the correlations with other constructs in the structural model. This means that the AVE value of an individual latent construct should be greater than the squared correlations with other latent constructs in the model. Thus, each construct has more variance with its own block of items than with other constructs representing a distinct block of items (Henseler et al., 2009).

Nevertheless, recent research has shown that the Fornell and Larcker criterion, as well as cross-loadings are poor measures of discriminant validity (Henseler, Ringle & Sarstedt, 2015). For instance, a study by Henseler et al., (2015) revealed that both the Fornell and Larcker technique performed poorly, especially when the item loadings on a construct vary even if marginally (for example item loadings within the range of 0.65 to 0.85). Therefore, the heterotrait-monotrait ratio (HTMT) of correlations was proposed by Henseler et al. (2015) as a better alternative to evaluate discriminant validity. The HTMT ratio is defined as "… the mean value of the indicator correlations across constructs (i.e., the heterotrait–heteromethod correlations) relative to the (geometric) mean of the average correlations for the indicators measuring the same construct (i.e., the monotrait–heteromethod correlations)". (Hair et al., 2021 p. 7). A lower HTMT ratio is indicative of discriminant validity, whereas a higher HTMT ratio indicates a lack of discriminant validity. For constructs that are similar conceptually, a maximum threshold of 0.90 and below suggests discriminant validity is achieved. However, for constructs that are conceptually different, a more modest maximum limit of 0.85 and below indicates that discriminant validity was established (Hair et al., 2021; Henseler et al., 2015). In the present study, all three techniques (i.e., the popular Fornell & Larcker criterion, cross-loadings and the HTMT ratio of correlations proposed by Henseler et al., 2015) were applied. The results from the Tables (4.26, 4.27, 4.28) below indicate that discriminant validity has been established in this study in all the three criteria proposed by scholars (Henseler et al., 2015; Chin, 1998; Fornell & Larcker, 1981). Table 4.26 shows that AVE values for all constructs (bold text) are larger than their corresponding correlation coefficients (plain text), indicating satisfactory discriminant validity for this criterion. Furthermore, discriminant validity was also achieved based on the criterion of cross-loadings. All indicators load higher on their respective constructs (bold text) than with other constructs (plain text) in the model (Table 4.27). Finally, the HTMT ratio for all constructs were below the maximum threshold of 0.85 (Table 4.28), suggesting discriminant validity. The maximum correlation (0.8) was between general takaful adoption (GTA) and religiosity (RG) Thus, in all three criteria, discriminant validity was established.

Table 4.26: Fornell and Larcker Criterion

Constructs	1	2	3	4	5	6	7	8	9
Awareness	**0.758**								
Compatibility	0.348	**0.824**							
Complexity	-0.091	-0.185	**0.781**						
General Takaful Adoption	0.380	0.595	-0.196	**0.879**					
Government Support	-0.465	-0.266	-0.143	-0.300	**0.847**				
Relative Advantage	0.375	0.660	-0.193	0.608	-0.328	**0.775**			
Religiosity	0.340	0.653	-0.181	0.733	-0.311	0.635	**0.834**		
Social Influence	0.522	0.234	0.066	0.358	-0.557	0.329	0.351	**0.814**	
Uncertainty	0.018	-0.231	0.581	-0.167	-0.168	-0.149	-0.147	0.067	**0.801**

Table 4.27: Loadings and Cross-loadings

Constructs	Loadings	1	2	3	4	5	6	7	8	9
AW	AW1	**0.669**	0.202	0.018	0.202	-0.319	0.227	0.209	0.277	0.087
	AW2	**0.782**	0.415	-0.177	0.378	-0.313	0.421	0.335	0.346	-0.039
	AW3	**0.784**	0.319	-0.046	0.282	-0.396	0.301	0.278	0.492	0.065
	AW4	**0.750**	0.367	-0.238	0.400	-0.287	0.381	0.416	0.287	-0.195
	AW5	**0.819**	0.213	0.062	0.276	-0.373	0.233	0.153	0.479	0.102
	AW6	**0.813**	0.182	-0.018	0.240	-0.388	0.243	0.181	0.496	0.077
	AW7	**0.691**	0.036	0.082	0.144	-0.447	0.130	0.136	0.441	0.188
	AW8	**0.745**	0.097	0.002	0.183	-0.427	0.109	0.152	0.465	0.070
CP	CP1	0.273	**0.849**	-0.192	0.492	-0.208	0.575	0.564	0.224	-0.150
	CP2	0.303	**0.875**	-0.160	0.568	-0.211	0.567	0.576	0.161	-0.244
	CP3	0.348	**0.859**	-0.194	0.515	-0.238	0.582	0.547	0.196	-0.184
	CP4	0.244	**0.744**	-0.158	0.414	-0.188	0.522	0.493	0.203	-0.195
	CP5	0.256	**0.786**	-0.049	0.442	-0.253	0.469	0.508	0.194	-0.172
CX	CX2	0.042	-0.041	**0.561**	-0.034	-0.118	-0.050	0.020	0.047	0.339
	CX3	-0.020	-0.093	**0.785**	-0.102	-0.162	-0.138	-0.108	0.104	0.442
	CX5	-0.124	-0.209	**0.948**	-0.221	-0.107	-0.198	-0.206	0.037	0.556
AI	AI1	0.338	0.583	-0.189	**0.915**	-0.296	0.548	0.684	0.305	-0.182
	AI2	0.355	0.506	-0.163	**0.897**	-0.248	0.501	0.673	0.361	-0.140
	AI3	0.362	0.575	-0.196	**0.920**	-0.289	0.571	0.700	0.361	-0.152
	AI4	0.273	0.405	-0.134	**0.775**	-0.215	0.521	0.494	0.214	-0.106
GS	GS1	-0.363	-0.162	-0.167	-0.202	**0.823**	-0.273	-0.194	-0.462	-0.200
	GS2	-0.409	-0.219	-0.064	-0.242	**0.851**	-0.288	-0.293	-0.498	-0.122
	GS3	-0.428	-0.238	-0.108	-0.287	**0.878**	-0.275	-0.266	-0.478	-0.132
	GS4	-0.453	-0.264	-0.108	-0.297	**0.885**	-0.325	-0.318	-0.497	-0.100
	GS5	-0.367	-0.205	-0.171	-0.192	**0.815**	-0.199	-0.200	-0.464	-0.150
	GS6	-0.330	-0.241	-0.132	-0.273	**0.830**	-0.285	-0.277	-0.440	-0.174
RA	RA1	0.290	0.476	-0.158	0.452	-0.283	**0.662**	0.510	0.281	-0.010
	RA2	0.271	0.430	-0.230	0.425	-0.261	**0.722**	0.503	0.193	-0.129
	RA3	0.351	0.549	-0.126	0.510	-0.295	**0.851**	0.526	0.330	-0.108
	RA4	0.304	0.491	-0.155	0.479	-0.259	**0.829**	0.501	0.240	-0.133
	RA5	0.175	0.449	-0.051	0.363	-0.191	**0.681**	0.344	0.119	-0.012
	RA6	0.313	0.559	-0.194	0.512	-0.263	**0.817**	0.493	0.295	-0.204
	RA7	0.302	0.600	-0.123	0.529	-0.223	**0.838**	0.541	0.287	-0.175
RG	RG1	0.246	0.601	-0.180	0.644	-0.284	0.586	**0.854**	0.319	-0.172
	RG2	0.277	0.552	-0.226	0.618	-0.221	0.568	**0.866**	0.260	-0.168
	RG3	0.248	0.484	-0.136	0.586	-0.214	0.474	**0.842**	0.213	-0.153
	RG4	0.314	0.532	-0.119	0.578	-0.255	0.519	**0.825**	0.276	-0.092
	RG5	0.301	0.540	-0.072	0.567	-0.356	0.512	**0.791**	0.365	-0.048
	RG6	0.315	0.553	-0.161	0.663	-0.232	0.513	**0.825**	0.322	-0.096

Table 4.27, continued

Constructs	Loadings	1	2	3	4	5	6	7	8	9
SI	SI1	0.491	0.184	-0.009	0.307	-0.478	0.304	0.318	**0.804**	0.024
	SI2	0.456	0.184	0.051	0.275	-0.508	0.311	0.280	**0.828**	0.086
	SI3	0.377	0.078	0.130	0.168	-0.488	0.209	0.182	**0.801**	0.176
	SI4	0.408	0.236	0.092	0.277	-0.391	0.228	0.284	**0.800**	0.036
	SI5	0.402	0.229	0.049	0.303	-0.418	0.300	0.356	**0.819**	0.017
	SI6	0.441	0.188	0.045	0.348	-0.467	0.276	0.306	**0.874**	0.028
	SI7	0.374	0.156	0.118	0.199	-0.441	0.201	0.203	**0.779**	0.067
	SI8	0.406	0.263	-0.003	0.344	-0.446	0.309	0.313	**0.801**	0.018
	SI9	0.441	0.135	0.083	0.303	-0.464	0.224	0.254	**0.813**	0.110
UC	UC1	0.002	-0.092	0.399	0.005	-0.095	0.027	-0.046	-0.010	**0.599**
	UC2	0.034	-0.209	0.427	-0.131	-0.110	-0.112	-0.144	0.073	**0.816**
	UC3	0.043	-0.208	0.437	-0.199	-0.110	-0.121	-0.143	0.020	**0.865**
	UC4	0.005	-0.203	0.541	-0.115	-0.177	-0.115	-0.110	0.048	**0.842**
	UC5	-0.002	-0.164	0.582	-0.102	-0.191	-0.184	-0.112	0.097	**0.820**
	UC6	-0.037	-0.160	0.516	-0.096	-0.153	-0.095	-0.080	0.073	**0.836**

Table 4.28: HTMT Ratio

Constructs	1	2	3	4	5	6	7	8	9
Awareness									
Compatibility	0.334								
Complexity	0.141	0.188							
General Takaful Adoption	0.382	0.657	0.180						
Government Support	0.528	0.291	0.200	0.320					
Relative Advantage	0.371	0.743	0.197	0.680	0.358				
Religiosity	0.337	0.726	0.176	0.800	0.334	0.702			
Social Influence	0.583	0.252	0.117	0.370	0.604	0.347	0.368		
Uncertainty	0.145	0.239	0.700	0.153	0.193	0.162	0.143	0.098	

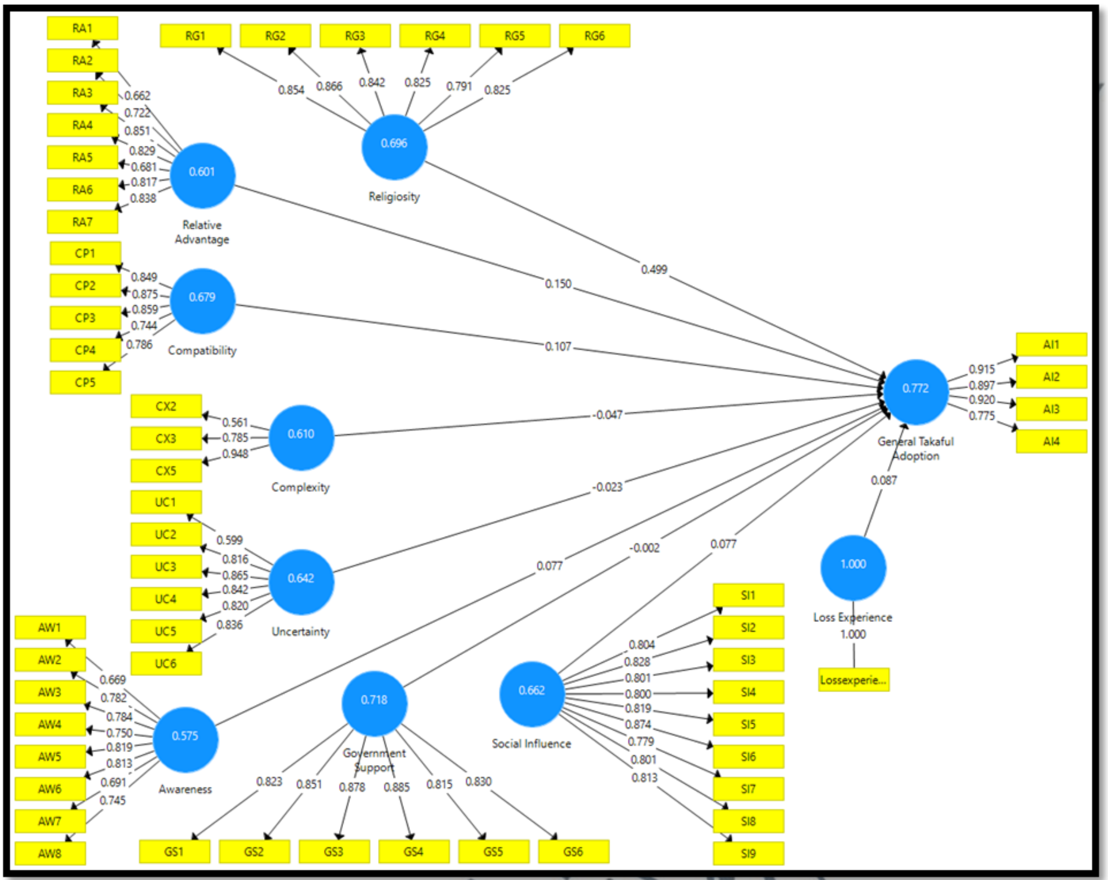

Figure 4.3: Measurement (Outer) Model

In general, reliability and validity of the measurement model was established in this study. The next step in assessing PLS-SEM results is to evaluate the structural model.

4.8.2 Structural Model Evaluation

Evaluating the structural model entails testing the significance and importance of the relationships among latent constructs (i.e., hypotheses testing). Also, the explanatory and predictive relevance of the research model is verified in this stage (Hair et al., 2021). The main statistical tests to evaluate the structural model in PLS-SEM includes the inspection of the following: significance of path coefficients in the model, the coefficient of determination (R2), the effect size (f2), predictive relevance (Q2), goodness of fit (GoF) of the model, and the out-of-sample predictive relevance (PLSpredict) (Hair et al., 2021; Hair et al., 2019). PLS-SEM as a non-parametric approach relies on the bootstrapping procedure which does not depend on any distributional assumptions to estimate the significance of the path coefficients (Hair et al., 2021). This study relied on the bootstrapping procedure (5000 bootstrap samples with 295 cases) to calculate the t-values of path coefficients. Subsequently, these t-values were evaluated based on the critical values from the standard normal distribution to decide whether the path coefficients are statistically significant. To evaluate the significance and relevance of the relationships among the constructs in the structural model, the significance level was set at $p<0.05$ and $p<0.01$ (1-tailed) (Hair et al., 2014). The structural model in this study consisted of the main effects model wherein the direct relationships between the exogenous and the endogenous constructs were evaluated, and the interaction model wherein the moderating effects of religiosity was tested on the relationships between the exogenous constructs and general takaful adoption. The results for the structural model are shown in Figure 4.4 and Table 4.29 for the main effects and Figure 4.9 and Table 4.34 for the moderating effects, respectively. Moreover, the model fit (GoF) was assessed prior to the test of significance (i.e., hypotheses testing) as recommended by Henseler, Hubona and Ray (2016). Henseler et al. (2016) suggested that the standardized root mean square residual (SRMR) should be applied to evaluate the model fit. An SRMR value of less than 0.08 is recommended to achieve satisfactory model fit. An SRMR value of 0.066 which is less than the maximum threshold of 0.08 was achieved in this study, suggesting satisfactory model fit (Henseler et.al., 2016).

4.8.2.1 Hypotheses (Testing) of the Main Effects

The hypotheses for the main effects were developed based on the first research question mentioned in chapter one. Specifically, the first research question was: "Do relative advantage, compatibility, complexity, uncertainty, awareness, social influence, government support, religiosity, and prior loss experience influence general takaful adoption among MSMEs owner-managers in North-West Nigeria?". Based on this research questions, the following nine (9) hypotheses were developed:

H1: Relative advantage positively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H2: Compatibility positively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H3: Complexity negatively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H4: Uncertainty negatively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H5: Awareness positively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H6: Social influence positively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H7: Government support positively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H8: Religiosity positively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

H9: Prior loss experience positively influences the adoption of general takaful among MSMEs owner-managers in North-West Nigeria.

Thus, the results of significance test were used to accept/reject these hypotheses advanced. Hypothesis 1 predicted that relative advantage has a positive influence on the adoption of general takaful. The results from Figure 4.4 and Table 4.29 show that relative advantage had a significant and positive influence on general takaful adoption among MSME owner-managers in North-West Nigeria (β =0.150; t =2.616; $p < 0.01$), supporting hypothesis 1. Hypothesis 2 predicted that compatibility has a significant and positive influence on general takaful adoption. The findings from Figure 4.4 and Table 4.29 reveal that compatibility had a significant and positive influence on general takaful adoption among MSME owner-managers in North-West Nigeria (β =0.107; t =1.926; $p < 0.05$) substantiating hypothesis 2. Furthermore, hypothesis 3 predicted that complexity has a significant and negative influence on general takaful adoption. The results from Figure 4.4 and Table 4.29 indicate that complexity had an insignificant influence on general takaful adoption among MSME owner-managers in North-West Nigeria (β = -0.047; t =1.029; $p > 0.05$), negating hypothesis 3. Similarly, hypothesis 4 predicted that uncertainty has a significant and negative influence on general takaful adoption. Figure 4.4 and Table 4.29 show that uncertainty had no significant negative influence on general takaful adoption among MSME owner-managers in North-West Nigeria (β = -0.023; t = 0.452; $p > 0.05$), therefore hypothesis 4 was not supported. Additionally, hypothesis 5 predicted that awareness has a significant and positive influence on general takaful adoption. The findings (Figure 4.4 and Table 4.29) showed that awareness had a significant and positive effect on general takaful adoption among MSME owner-managers in North-West Nigeria (β =0.077; t =1.724; $p < 0.05$), corroborating hypothesis 5. Also, hypothesis 6 predicted that social influence has a significant and positive impact on general takaful adoption. The results (Figure 4.4 and Table 4.29) reveal that social influence had a significant and positive influence on general takaful adoption among MSME owner-managers in North-West Nigeria (β =0.077; t =1.813; $p < 0.05$), substantiating hypothesis 6. For hypothesis 7, it was hypothesized that government support has a significant and positive effect on general takaful adoption. From the results (Figure 4.4 and Table 4.29) government support had no significant positive influence on general takaful adoption among MSME owner-managers in North-West Nigeria (β = -0.002; t =0.044; $p > 0.05$). Consequently, hypothesis 7 was not supported. The next hypothesis predicted that religiosity would have a significant and positive impact on general takaful adoption. Findings (Figure 4.4 and Table 4.29) indicate that religiosity had a significant and positive impact on general takaful adoption among MSME owner-managers in North-West Nigeria (β =0.499; t =7.738; $p < 0.01$), validating hypothesis 8. The final hypothesis (hypothesis 9) in the main effect model predicts that prior loss experience has a significant positive influence on general takaful adoption. Results from Figure 4.4 and Table 4.29 indicate that prior loss experience had a positive significant influence on general takaful adoption among MSME owner-managers in North-West Nigeria (β =0.087; t =2.202; $p < 0.01$), supporting hypothesis 9.

Furthermore, the results of hypotheses testing in the main effect model (Figure 4.4 and Table 4.29) established that among the nine exogenous constructs predicting general takaful adoption, religiosity had the highest standardized beta coefficient (0.499), denoting that religiosity was the most important construct in predicting general takaful adoption among MSME owner-managers in North-West Nigeria.

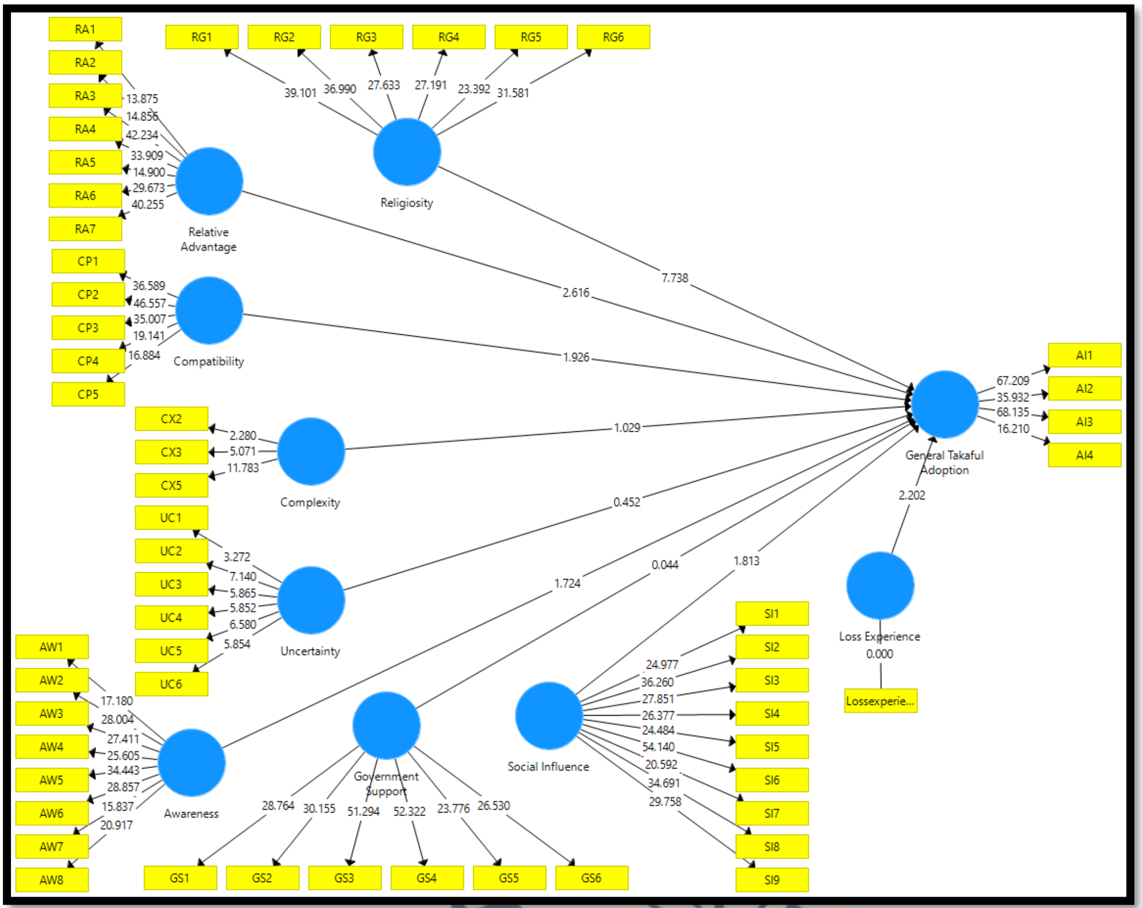

Figure 4.4: Structural Model (Main Effects)

Table 4.29: Structural Model Evaluation (Main Effects)

H (±)	Relationships	Std. Beta	Std. Error	t-values	p-values	Decision
H1(+)	Relative Advantage → General Takaful Adoption	0.150	0.057	2.616**	0.005	Supported
H2 (+)	Compatibility → General Takaful Adoption	0.107	0.055	1.926*	0.028	Supported
H3 (-)	Complexity → General Takaful Adoption	-0.047	0.046	1.029	0.153	Not Supported
H4 (-)	Uncertainty → General Takaful Adoption	-0.023	0.052	0.452	0.326	Not Supported
H5 (+)	Awareness → General Takaful Adoption	0.077	0.045	1.724*	0.044	Supported
H6 (+)	Social Influence → General Takaful Adoption	0.077	0.042	1.813*	0.036	Supported
H7 (+)	Government Support → General Takaful Adoption	-0.002	0.041	0.044	0.483	Not Supported
H8 (+)	Religiosity → General Takaful Adoption	0.499	0.065	7.738**	0.000	Supported
H9 (+)	Loss Experience → General Takaful Adoption	0.087	0.039	2.202**	0.015	Supported

Note: **Significant at 0.01 (1-tailed), *Significant at 0.05 (1-tailed)

4.8.2.2 Assessment of Variance Explained in the Endogenous Construct (R^2)

After evaluating the significance of the path coefficients, the next step is to examine the explanatory power of the model. The coefficient of determination (R^2) (also called the in-sample predictive power) is the standard used to evaluate the explanatory power of the structural model (Hair et al., 2021). The R^2 value refers to the proportion of variance in the endogenous variable which can be accounted for by the predictor variables in the structural model (Hair et al., 2014). The value of R^2 ranges between 0 and 1, and the closer to one the R^2 is, the higher the explanatory power of the model. There is no agreed standard among scholars of a satisfactory R^2 value. However, Hair et al., (2021; 2014) argue that the research context and discipline should guide the decision of the adequacy of the R^2 value. Hair et al. (2021) further elaborated that an R^2 value of 0.10 is regarded as satisfactory in stock returns prediction. Furthermore, Falk and Miller (1992) suggested a minimum threshold R^2 value of 0.10 is considered as acceptable. Additionally, Cohen (1988) provided a general guideline for acceptable R^2 value as follows: 0.02 (weak), 0.13 (moderate) and 0.26 (substantial). Also, Hair et al (2011) suggested that R^2 values of 0.25, 0.50, and 0.75 can be classified as weak, moderate and substantial, respectively, in many social science research studies. Moreover, Chin (1998) also proposed acceptable R^2 values for PLS-SEM as follows: 0.19 (weak), 0.33 (moderate), and 0.67 (substantial). Table 4.30 presents the R^2 values for the main effect model for this study. The results show that the model explains 60% (0.60) of the variance in the endogenous construct (main effect model). Thus, based on the guidelines proposed above, the main effect model can be considered moderate (Hair et al., 2011; Chin, 1998) or substantial according to the standards of Cohen (1988).

Table 4.30: Variance Explained in the Endogenous Construct

Endogenous Construct	Construct Variance Explained (R^2)
General Takaful Adoption (Main effect)	60%

4.8.2.3 Assessment of the Effect Size (f^2)

Another means of assessing the explanatory power of the structural model is by examining the change in the R^2 value when a given predictor variable is excluded from the model. This measure of evaluation is known as the effect size (f2). The unique contribution of each predictor variable in the model is known through the effect size (f^2) assessment (Sarstedt et.al., 2017). Essentially, effect size is used to demonstrate the practical significance of predictor variables in real life scenario. The f^2 is calculated based on the following formula (Cohen, 1988).

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

(4.1)

Where R^2 included and R^2 excluded refer to the R^2 values of the independent variable when a given independent variable is included or excluded from the structural model. Furthermore, the denominator value of 1 represents a constant term. Cohen (1988) provided a general standard for the evaluation of f^2 values as follows: 0.02 (small effect), 0.15 (medium effect), and 0.35 (large effect), respectively. Values of f^2 below 0.02 threshold are considered as no effect. Table 4.31 below shows the f^2 values of the predictor variables in the study. Following the guideline of Cohen (1988), the results show that the effect sizes of the predictor variables can be categorized as (1) none (compatibility=0.013, complexity=0.003, uncertainty=0.001, awareness=0.009, social influence=0.008, & government support=0.000), (2) small (relative advantage=0.026 & prior loss experience=0.020), and (3), and medium (religiosity=0.296), respectively.

Table 4.31: Effect Size (f^2) (Main Effect Model)

Effect Size	f^2	Size
Awareness	0.009	None
Compatibility	0.013	None
Complexity	0.003	None
Government Support	0.000	None
Loss Experience	0.020	Small
Relative Advantage	0.026	Small
Religiosity	0.296	Medium
Social Influence	0.008	None
Uncertainty	0.001	None

4.8.2.4 Construct Cross-validated Redundancy (Q2)

Since PLS-SEM is more inclined to prediction and explanation of variance in the endogenous variable, the assessment of the predictive relevance of the model is essential. In PLS-SEM, the predictive relevance of the structural model is evaluated based on cross-validated redundancy (Q^2) blindfolding procedure (Geisser, 1974; Stone, 1974). To calculate the Q^2 value in this study, the cross-validated redundancy approach was employed using SmartPLS 3.3.3 with an omission distance of 7 (Sarstedt et al., 2017). The blindfolding procedure predicts and imputes the omitted data points and re estimate the model parameters (Hair et al., 2019; Sarstedt et al., 2017). To get a high Q^2 value (i.e., high predictive relevance) the difference between the predicted and original values should be small. The smaller the variance, the higher the predictive accuracy (Q^2) of the structural model (Sarstedt et al., 2017). Q^2 value greater than zero for an endogenous latent variable signify an acceptable predictive accuracy (Hair et al., 2019). Like f^2 effect size, Q^2 effect size can be computed to examine the change in the Q2 value when a given exogenous variable is excluded from the structural model. As a general guide, predictor variables with Q^2 values of 0.02, 0.15, and 0.35 are considered to have small, medium, and large predictive relevance, respectively, on a criterion variable in a structural model (Sarstedt et al. 2017; Chin, 1998). The Q^2 value for this study is shown in Table 4.32 below. The result (column labelled 1-SSE/SSO) revealed that the Q^2 value for the study's endogenous variable was above zero (Q^2=0.472), indicating a high predictive accuracy and relevance of the model (Sarstedt et al., 2017; Chin, 1998).

Table 4.32: Construct Cross-Validated Redundancy (Q^2)

Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
General takaful Adoption	1356	715.491	0.472

4.8.2.5 Out-of-Sample Predictive Power (PLSpredict)

The prediction orientation of many research studies using PLS-SEM approach requires not only the estimation of the structural model's in-sample explanatory power (R^2) but also its out-of-sample predictive power (PLSpredict). A model's out-of-sample predictive power refers to the capability of a model to "predict the values of new or future observations" which are not incorporated in the estimation process (Hair et al., 2021 p. 119). The R^2 value has been commonly used by researchers as the criterion for evaluating a model's predictive power. However, this assertion is only valid for in-sample prediction and does not include the model's ability to predict new and future cases (Hair et al., 2019; Shmueli et al., 2019). Furthermore, the Q^2 value, which is another means of assessing the structural model's predictive power suffers from the same drawback as R^2. The calculation of the Q2 value "does not draw on holdout samples, but on single data points (as opposed to entire observations) being omitted and imputed. Hence, the Q2 value can only be partly considered as a measure of out-of-sample prediction, because the sample structure remains largely intact in its computation" (Sarstedt et al., 2017 p. 21). To overcome this limitation, Shmueli et al., (2016) developed PLSpredict procedure to estimate out-of-sample prediction in PLS-SEM. The PLSpredict procedure "involves estimating the model on an analysis (i.e. training) sample and evaluating its predictive performance on data other than the analysis sample, referred to as a holdout sample" (Hair et al., 2019 p.12). Given the increasing importance assigned to a study's practical usefulness, researchers should as a matter of routine, incorporate the out-of-sample prediction as part of the structural model evaluation in PLS-SEM (Shmueli et al., 2019).

The root-mean-square error (RMSE) metric and the mean absolute error (MAE) metric are the two popular prediction statistic measures applied to assess the degree of prediction error in the measurement items of a given independent construct. However, the RMSE is the preferred choice in PLS-SEM approach (Hair et al., 2021; Shmueli et al., 2019). The PLSpredict procedure applies these metrics to evaluate the structural model's out-of-sample predictive relevance. To evaluate the model's predictive power using these metrics, the RMSE (or MAE) values of the measurement items of the dependent construct should be "compared with a naïve linear regression model (LM) benchmark" (Hair et al., 2021 p. 121). To interpret and understand the comparison, the following guidelines are used (Shmueli et al., 2019):

1. If all measurement items of the independent construct in the PLS-SEM model have lower RMSE (or MAE) values compared to the naïve LM benchmark, the model has high predictive power.
2. If most of the measurement items of the independent construct have lower RMSE (or MAE) values in PLS-SEM model compared to the LM benchmark, the model has medium predictive power.

3. If only few of the endogenous construct indicators in the PLS-SEM model have lower prediction errors (RMSE) compared to the LM standard, the model has low predictive power.
4. If none of the indicators of the dependent construct in the PLS-SEM model has lower prediction errors (RMSE) compared to the LM benchmark, the model has no predictive power.

Table 4.33 shows the results of PLSpredict procedure. All indicators in the PLS-SEM model (RMSE column) have lower prediction errors compared to the LM benchmark (RMSE column), indicating the model's high predictive power (Shmueli et al., 2019).

Table 4.33: Out-of-Sample Predictive Power (PLSpredict)

	PLS			**LM**			**PLS-LM**		
Items	**RMSE**	**MAE**	**Q^2_predict**	**RMSE**	**MAE**	**Q^2_predict**	**RMSE**	**MAE**	**Q^2_predict**
AI1	1.284	0.957	0.518	1.403	1.015	0.424	-0.119	-0.058	0.094
AI2	1.295	0.923	0.440	1.369	0.953	0.374	-0.074	-0.030	0.066
AI3	1.261	0.943	0.544	1.333	0.970	0.491	-0.072	-0.027	0.053
AI4	1.604	1.221	0.338	1.682	1.257	0.272	-0.078	-0.036	0.066

4.8.2.6 Hypotheses Testing (Moderating Effects)

The final stage in the analysis process is to evaluate the moderating effect of religiosity on the research model. The hypotheses for the moderating effects were formulated based on the second research question mentioned earlier in chapter one. Specifically, the second research question was: "Does religiosity moderate the relationship between relative advantage, compatibility, complexity, uncertainty, awareness, social influence, government support, prior loss experience and general takaful adoption among MSMEs owner-managers in North-West Nigeria?". From these research questions eight (8) hypotheses were developed as follows:

H10a: Religiosity moderates the positive relationship between relative advantage and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity.

H10b: Religiosity moderates the positive relationship between compatibility and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity.

H10c: Religiosity moderates the negative relationship between complexity and general takaful adoption. Specifically, this relationship will be weaker for MSME owner-managers with high religiosity than those with low religiosity.

H10d: Religiosity moderates the negative relationship between uncertainty and general takaful adoption. Specifically, this relationship will be weaker for MSME owner-managers with high religiosity than those with low religiosity.

H10e: Religiosity moderates the positive relationship between awareness and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity.

H10f: Religiosity moderates the positive relationship between social influence and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity.

H10g: Religiosity moderates the positive relationship between government support and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity.

H10h: Religiosity moderates the positive relationship between prior loss experience and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity.

To validate these hypotheses, the significance of path coefficients in the moderating effect structural model was examined. To calculate the interaction term (moderating effects) the product-indicator approach (Hair et al., 2021) in SmartPLS 3.3.3 was used. Figure 4.5 and Table 4.34 show the results of the moderation analysis. The first moderation hypothesis (H10a) predicts that the positive influence of relative advantage on general takaful adoption will be moderated by religiosity, such that the impact will be stronger for MSME owner-managers with high religiosity than those with low religiosity. The results (Figure 4.9, Table 4.34) of interaction term (RA*RG-> GTA) was statistically significant (($\beta = 0.179$, $t = 2.047$, $p < 0.01$). Hence, Hypothesis 10a was supported. Additionally, it is recommended to use the simple slope analysis to interpret the results of moderating effects (Hair et al., 2021). Consequently, the simple slopes graph (Dawson, 2013) was plotted using two-way interaction with continuous moderator to evaluate the moderating effects. The simple slope plot (Figure 4.5) reveals that the influence of relative advantage on general takaful adoption is stronger among MSME owner-managers with high religiosity (i.e., the relative advantage-general takaful adoption slope becomes steeper with high religiosity) than those with low religiosity (i.e., shallow slope). This means that an MSME owner-manager’s religiosity influences the perception of relative advantage of general takaful. Those with high religiosity rate general takaful positively on relative advantage more than those that exhibit low religiosity.

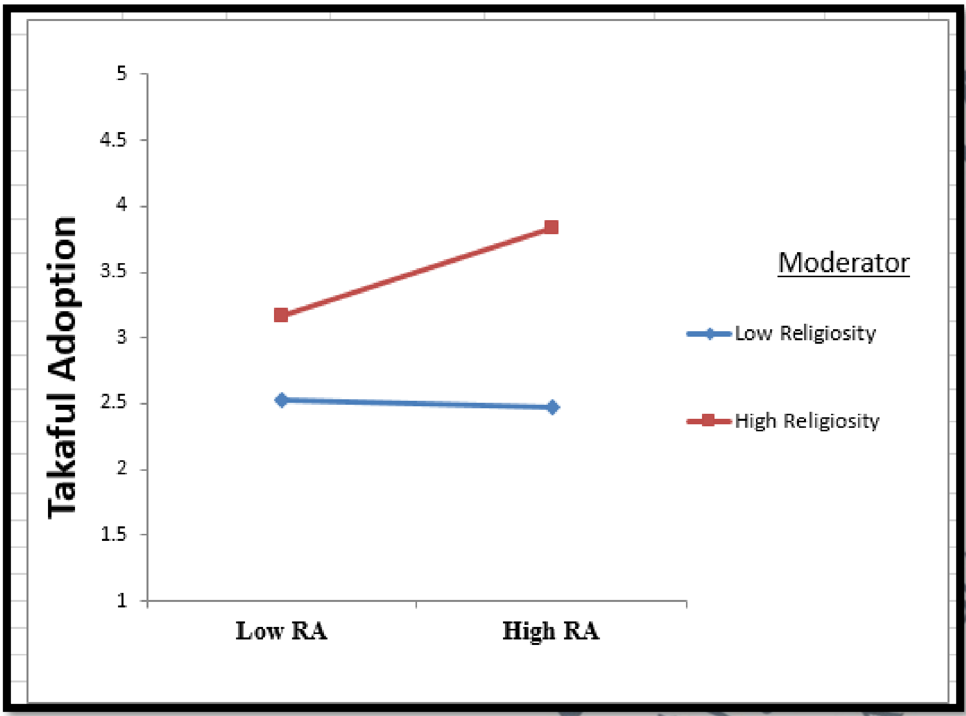

Figure 4.5: Interaction effect of Relative Advantage and Religiosity on General Takaful Adoption

Furthermore, hypothesis H10c predicts that the negative influence of complexity on general takaful adoption will be moderated by religiosity, such that the impact will be weaker for MSME owner-managers with high religiosity than those with low religiosity. Figure 4.9 and Table 4.34 showed that the interaction term (CX *RG-> GTA) was statistically significant (($\beta = 0.086$, $t = 1.926$, $p < 0.05$). Hence, Hypothesis 10c was supported in this study. Moreover, the simple slope analysis was applied to interpret the results of moderating effects (Hair et al., 2021). The simple slopes graph (Dawson, 2013) was plotted using two-way interaction with continuous moderator to evaluate the moderating effects. The simple slope plot (Figure 4.6) showed that the influence of complexity on general takaful adoption is weaker among MSME owner-managers with high religiosity (i.e., the complexity-general takaful adoption slope becomes shallower with high religiosity) than those with low religiosity (i.e., steeper slope). This means that an MSME owner-manager's religiosity influences the perception of complexity of general takaful. Those high in religiosity rate general takaful complexity low when compared to those that exhibit low religiosity.

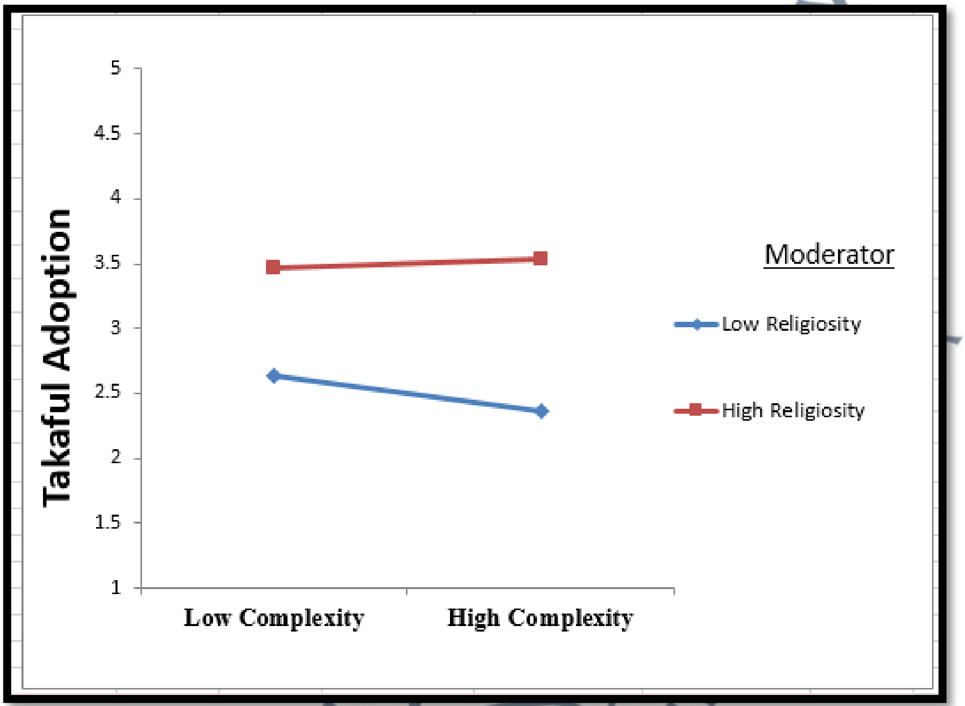

Figure 4.6: Interaction effect of Complexity and Religiosity on General Takaful Adoption

Also, hypothesis 10g predicted that the positive influence of government support on general takaful adoption will be moderated by religiosity, such that the impact will be stronger for MSME owner-managers with high religiosity than those with low religiosity. The results from Figure 4.9 and Table 4.34 showed that the interaction term (GS*RG-> GTA) was statistically significant (($\beta = 0.188$, $t = 3.464$, $p < 0.01$). Hence, hypothesis 10g was validated in this study. Likewise, the simple slope analysis was applied to interpret the results of moderating effects (Hair et al., 2021). The simple slopes graph (Dawson, 2013) was plotted using two-way interaction with continuous moderator to evaluate the moderating effects. The simple slope plot (Figure 4.7) showed that the influence of government support (which was statistically insignificant in the main effects model) on general takaful adoption is stronger among MSME owner-managers with high religiosity (i.e., the government support-general takaful adoption red slope becomes steeper with high religiosity). As for those with low religiosity (i.e., blue slope) the impact of government support on takaful adoption is weaker (i.e., low religiosity weakens the positive influence of government support on takaful adoption). This suggests that government activities in terms of regulatory, legal, and incentive support for general takaful will have a strong and positive impact on MSME owner-manager's that exhibit high religiosity as compared to those with low religiosity.

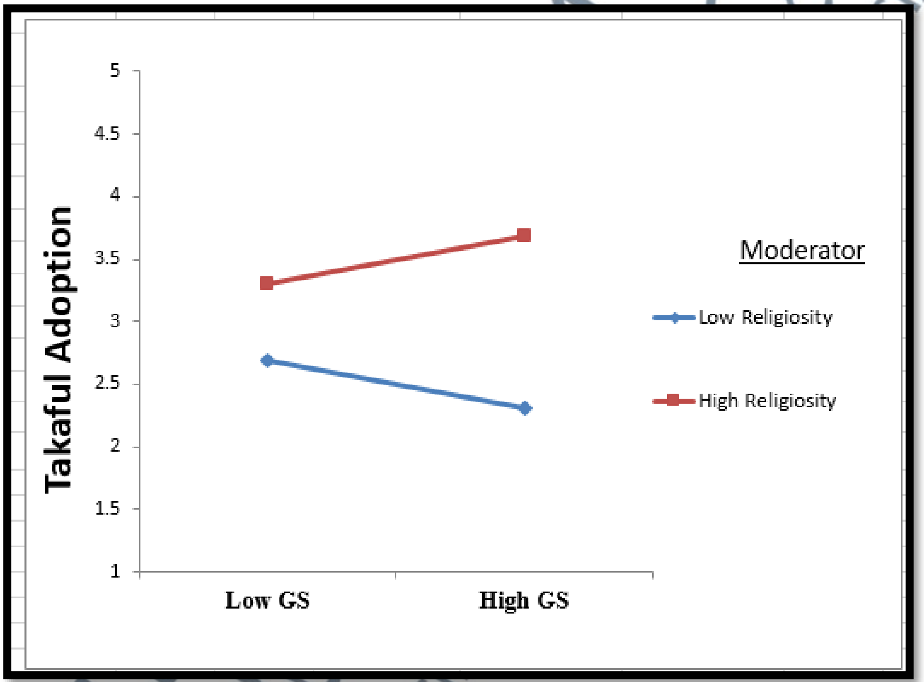

Figure 4.7: Interaction effect of Government Support and Religiosity on General Takaful Adoption

Hypothesis 10h predicted that the positive influence of prior loss experience on general takaful adoption will be moderated by religiosity, such that the impact will be stronger for MSME owner-managers with high religiosity than those with low religiosity. The findings (Figure 4.9 and Table 4.34) showed that the interaction term (LE*RG-> GTA) was statistically significant ($\beta = 0.068$, $t = 1.812$, $p < 0.05$). Hence, Hypothesis 10h was confirmed in this study. Likewise, the simple slope analysis was used to interpret the findings of moderating effects (Hair et al., 2021). The simple slopes graph (Dawson, 2013) was plotted using two-way interaction with continuous moderator to evaluate the moderating effects. The simple slope plot (Figure 4.8) showed that the influence of prior loss experience on general takaful adoption is stronger among MSME owner-managers with high religiosity (i.e., the prior loss experience-general takaful adoption slope[red] becomes steeper with high religiosity) than those with low religiosity (i.e., shallow[blue] slope). This implies that the influence of loss experience on general takaful adoption is stronger among MSME owner-managers exhibiting high religiosity than those with low religiosity.

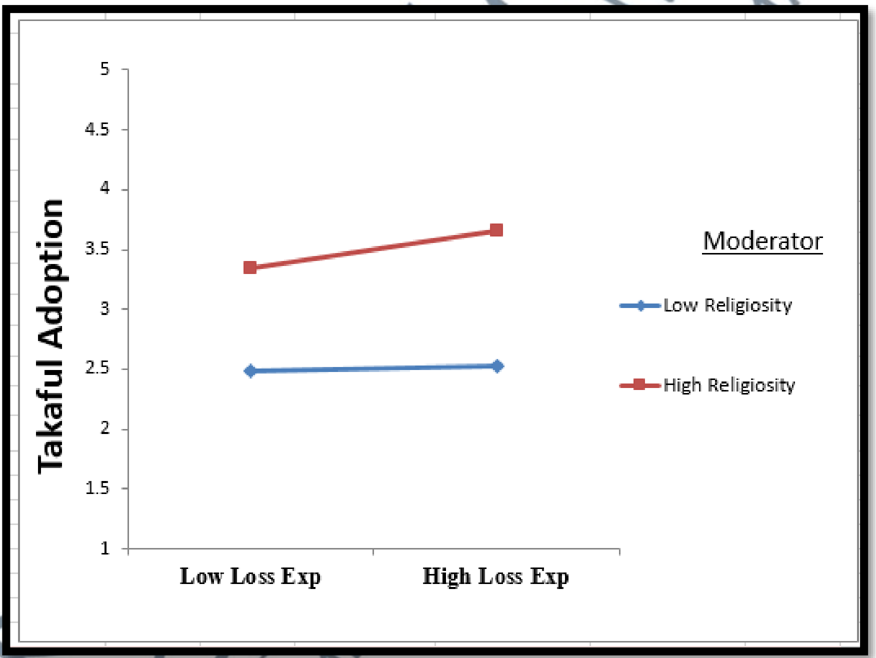

Figure 4.8: Interaction effect of Prior Loss Experience and Religiosity on General Takaful Adoption

However, the other moderating effect hypotheses were not substantiated in this study. Specifically, hypothesis 10b predicted that the positive influence of compatibility on general takaful adoption will be moderated by religiosity, such that the impact will be stronger for MSME owner-managers with high religiosity than those with low religiosity. Surprisingly, the finding (Figure 4.9 and Table 4.34) was contrary to the hypothesized relationship. The impact of compatibility on general takaful adoption was stronger (instead of weaker) for MSME owner-managers with low religiosity than those with high religiosity. Although, the relationship (CP*RG-> GTA) was statistically significant ($\beta = -0.139$, $t = 2.468$, $p < 0.01$), the hypothesis was not supported. This unexpected finding was further discussed in the subsequent chapter.

Similarly, Hypothesis 10e predicted that the positive influence of awareness on general takaful adoption will be moderated by religiosity, such that the impact will be stronger for MSME owner-managers with high religiosity than those with low religiosity. However, the findings obtained (Figure 4.9 and Table 4.34) from the interaction term (AW*RG-> GTA) was statistically insignificant ($\beta = -0.109$, $t = 1.612$, $p > 0.05$) and therefore the hypothesis was not validated in this study.

Furthermore, Hypothesis 10d postulated that the negative influence of uncertainty on general takaful adoption will be moderated by religiosity, such that the impact will be weaker for MSME owner-managers with high religiosity than those with low religiosity. This hypothesis was not validated in this study ($\beta = 0.032$, $t = 0.585$, $p > 0.05$). Equally, hypothesis 10f which postulated that the positive effect of social influence on general takaful adoption will be moderated by religiosity, such that the impact will be stronger for MSME owner-managers with high religiosity than those with low religiosity. The finding (Figure 4.9 and Table 4.34) in this study did not substantiate this hypothesis ($\beta = 0.041$, $t = 0.689$, $p > 0.05$).

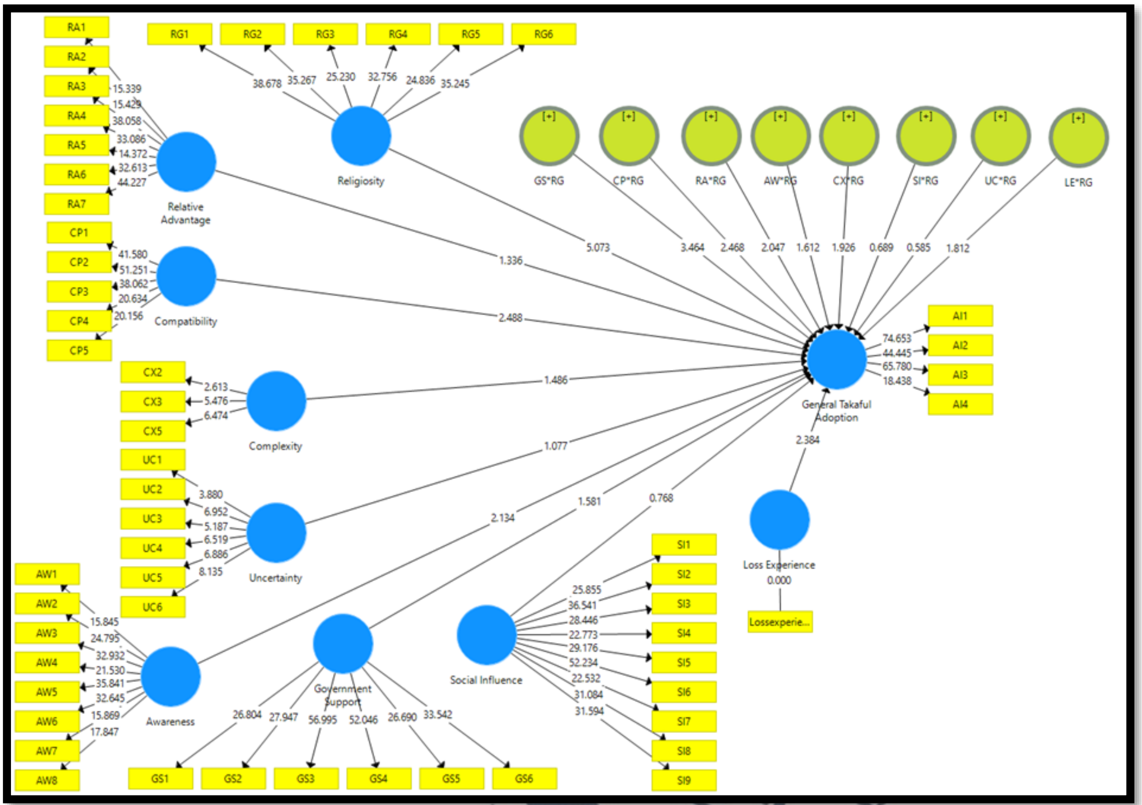

Figure 4.9: Structural Model (Moderating Effects)

Table 4.34: Structural Model Evaluation (Moderating Effects)

Hypotheses	**Relationships**	**Std. Beta**	**Std. Error**	**t-values**	**p-values**	**Decision**
H10a	RA*RG → General Takaful Adoption	0.179	0.088	2.047**	0.022	Supported
H10b	CP*RG → General Takaful Adoption	-0.139	0.056	2.468**	0.008	Not Supported
H10c	CX*RG → General Takaful Adoption	0.086	0.045	1.926*	0.028	Supported
H10d	UC*RG → General Takaful Adoption	0.032	0.054	0.585	0.280	Not Supported
H10e	AW*RG → General Takaful Adoption	-0.109	0.067	1.612	0.055	Not Supported
H10f	SI*RG → General Takaful Adoption	0.041	0.060	0.689	0.246	Not Supported
H10g	GS*RG → General Takaful Adoption	0.188	0.054	3.464**	0.000	Supported
H10h	LE*RG → General Takaful Adoption	0.068	0.037	1.812*	0.036	Supported

Note: **Significant at 0.01 (1-tailed), *Significant at 0.05 (1-tailed)

4.8.2.7 Evaluating the Strength of the Moderating Effects

The R^2 value of the direct effect model and the moderating effect model was compared to assess the level of impact the moderating variable (i.e., religiosity) has on the relationship between the predictor variables and general takaful adoption among MSMES owner-managers in North-West Nigeria (Wilden, Gudergan, Nielsen, & Lings, 2013). The following formula was used to calculate the strength of the moderator in the structural model (Cohen, 1988).

$$f^2 = \frac{R_i^2 - R_m^2}{1 - R_i^2}$$

(4.2)

where *i* = interaction model and *m* = main effect model.

Table 4.36 presents the effect size of the moderating effects model. The R2 value for the main model and the full model (including moderating effects) were 0.600 and 0.648, respectively. The effect size for the full model was 0.1364. The effect size of the moderating effects in this study can be regarded as small based on the guidelines of Cohen (1988). Cohen (1988) categorized effect size values as follows: small (0.02), medium (0.15), and large (0.35). However, Kenny (2018) and Hair et al. (2021) argued that standard effect sizes proposed by Cohen (1988) are not realistic when applied to interaction effects. Thus, Kenny (2018) proposed a more realistic standard for measuring the effect size of moderation as follows: “effect size values of 0.005, 0.01, and 0.025 should be considered as evidence for small, medium, and large effect sizes, respectively” (Hair et al., 2021 p. 162). Therefore, following this guideline, the effect size of the moderation effect model can be considered as large.

Furthermore, the effect sizes of each interaction of the predictor variables with the moderator in the full model was calculated in Smartpls 3.3.3. Table 4.36 shows the effect sizes of the interaction terms. The effect sizes as shown below range between none to small based on Cohen (1988) standard. However, based on the proposed cut-off standard by Kenny (2018) for interaction effects, the effect sizes range between none to large.

Table 4.35: Strength of the Moderating Effects Based on Kenny's (2018)

Endogenous Construct	**R^2 Included (interaction)**	**R^2 Excluded (main model)**	**f^2**
General Takaful Adoption	0.648	0.600	0.1364

Table 4.36: Effect Sizes of Interaction Effect Based on Kenny's (2018)

Relationships	f^2	Size
AW*RG	0.013	Small
CP*RG	0.020	Medium
CX*RG	0.012	Small
GS*RG	0.040	Large
LE*RG	0.012	Small
RA*RG	0.023	Medium
SI*RG	0.002	None
UC*RG	0.002	None

4.8.3 Summary of Findings

Having presented the results of both the main and moderating effects model evaluation in the previous sections, Table 4.37 presents the summary of findings for all the 17 hypotheses investigated in this study.

Table 4.37: Summary of Hypotheses Testing

Hypothesis	Statement	Finding
H1	Relative advantage positively influences the adoption of general takaful	Supported (Sig)
H2	Compatibility positively influences the adoption of general takaful	Supported (Sig)
H3	Complexity negatively influences the adoption of general takaful	Not Supported (N.Sig)
H4	Uncertainty negatively influences the adoption of general takaful	Not Supported (N.Sig)
H5	Awareness positively influences the adoption of general takaful	Supported (Sig)
H6	Social influence positively influences the adoption of general takaful	Supported (Sig)
H7	Government support positively influences the adoption of general takaful	Not Supported (N.Sig)
H8	Religiosity positively influences the adoption of general takaful	Supported (Sig)
H9	Prior loss experience positively influences the adoption of general takaful	Supported (Sig)

Table 4.37, continued

Hypothesis	Statement	Finding
H10a	Religiosity moderates the positive relationship between relative advantage and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity	Supported (Sig)
H10b	Religiosity moderates the positive relationship between compatibility and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity	Not Supported (Sig)
H10c	Religiosity moderates the negative relationship between complexity and general takaful adoption. Specifically, this relationship will be weaker for MSME owner-managers with high religiosity than those with low religiosity	Supported (Sig)
H10d	Religiosity moderates the negative relationship between uncertainty and general takaful adoption. Specifically, this relationship will be weaker for MSME owner-managers with high religiosity than those with low religiosity	Not Supported (N.Sig)
H10e	Religiosity moderates the positive relationship between awareness and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity	Not Supported (N.Sig)
H10f	Religiosity moderates the positive relationship between social influence and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity	Not Supported (N.Sig)
H10g	Religiosity moderates the positive relationship between government support and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity	Supported (Sig)
H10h	Religiosity moderates the positive relationship between prior loss experience and general takaful adoption. Specifically, this relationship will be stronger for MSME owner-managers with high religiosity than those with low religiosity	Supported (Sig)

4.9 Chapter Summary

The present chapter presents the analysis and results of the study. First, the chapter presented the preliminary analysis, including the descriptive profile of respondents. Second, the model was assessed in two stages. The measurement model was first evaluated to establish reliability, convergent and discriminant validity. Afterwards, the structural model was assessed to test the hypotheses advanced in previous chapters. A total of nine hypotheses were developed to test the direct influence of the predictor variables on general takaful adoption. Based on the results, six out of the nine alternate hypotheses were substantiated. Furthermore, eight hypotheses were developed to test the moderating effect of religiosity on the structural model. The findings showed that out of the eight alternate hypotheses, four were significant and supported. Moreover, the structural model predictive power was high based on the R^2, Q^2, and RMSE values realized in the study. The next chapter presents the discussion of findings, research implications, limitations, and conclusion.