CHAPTER 3

METHODOLOGY

3.1 Introduction

The previous chapter summarised and reviewed extensive literature to conclude current research from previous research by setting forward a research framework and hypotheses. This chapter describes the research philosophy paradigm, justifies the research design, and describes the research technique used to address the questions outlined in Chapter 1 and the literature review emphasised in Chapter 2. The final section of this chapter provides an overview of the data analysis procedure employing partial least squares structural equation modelling (PLS-SEM).

3.2 Research Approach and Design

The term "research philosophy" refers to a comprehensive notion that describes how knowledge develops and the nature of that knowledge. Research philosophy is beliefs about how evidence on a phenomenon should be obtained, analysed, interpreted, and employed (Holden & Lynch, 2004). Research designs are the plans and procedures for conducting research that ranges from general research hypotheses to specific techniques for data collection and analysis (Creswell, 2009). The process of designing a research study always begins with the selection of a topic and research paradigm (Creswell, 2009). A paradigm is a collection of assumptions that creates a conceptual framework or a philosophical worldview that allows us to explore the world around us in a systematic manner (Suppe, 1977).

According to Filstead (1979), as referenced by Deshpande (1983), Paradigms fulfil numerous functions. First and foremost, paradigms assist professionals by highlighting critical difficulties confronting any sector. Second, paradigms enable researchers to construct models and theories that allow them to tackle these problems. Third, paradigms provide requirements for tools like methodology, instruments, and data collection that will be used to deal with these issues. Finally, paradigms outline the concepts, procedures, and methods to follow if similar problems arise in the future.

The two main research paradigms—positivism and interpretivism—generally serve as the direction for researchers. Positivism is a systematic method of integrating deductive reasoning and specific empirical observations of individual behaviour to discover and establish a set of probabilistic causal laws that can explain general patterns of human activity (Neuman, 2003). In positivism, reality is separated from the researcher because the researcher presumes that reality is objective (Weber, 2004). Positivists frequently employ various techniques as their preferred research methodologies, including surveys, field experiments, and laboratory experiments. They aim to collect many data using these methods and typically use statistical analysis.

Contrarily, interpretivism presupposes that the researcher and reality are inextricably linked (Weber 2004), and interpretivists frequently comprehend and interpret from their frame of reference (Fitzgerald & Howcroft, 1998). Interpretivists typically employ hermeneutics and phenomenology to unravel ambiguous meanings and reflect on concealed ones. Among their favoured study methodologies are the case, ethnographic, phenomenographic, and ethnomethodological studies (Weber, 2004). Regarding research design, there are quantitative and qualitative methods (Neuman, 2014).

Quantitative research involves testing objective hypotheses by investigating the relationship between the constructs studied (Neuman, 2014). As a result, these constructions may be measured using instruments, and the resulting numerical data can be examined statistically. More recently, the quantitative approach has also included extended structural equation modelling (SEM) that incorporates causal pathways and the determination of the combined strength of many components (Creswell 2009). The demand to evaluate comprehensive theories and concepts has led to the growth in the popularity of SEM (Rigdon, 1998).

According to Creswell (2009), qualitative research is a way to investigate and understand the meaning that people or groups assign to social or human problems. Qualitative research integrates questions and procedures, where data are often obtained in the participant's setting. The researcher then evaluates the data after inductively building from particulars to general themes. The philosophical foundations of quantitative and qualitative research approaches vary, as do some of their methods, models, and procedures (Neuman, 2014). Comparing quantitative and qualitative research methods is summarized in Table 3-1 below.

Table 3-1: Differences between Quantitative and Qualitative Methods

Quantitative Research	Qualitative Research
Researchers test hypotheses that are stated at the beginning	Researchers capture and discover meaning once they become immersed in the data
Concepts are in the form of distinct construct	Concepts are in the form of themes, motifs generalizations, and taxonomies
Measurements are systematically created	Measurements are created in an ad hoc

before data collection and are standardized	manner and are often specific to the individual setting or researcher
Data are in the form of numbers from precise measurement	Data are in the form of words and images from documents, observations, and transcript
The theory is mainly causal and deductive	Theory can be causal or noncausal and is often inductive
Procedures are standard, and replication is frequent	Research procedures are particular, and replication is very rare
The analysis proceeds by using statistics, tables, or charts and discussing how what they show relates to hypotheses	Analysis proceeds by extracting themes or generalizations from evidence and organizing data to present a coherent and consistent picture

Source: Neuman (2014)

Despite the differences between quantitative and qualitative methods, neither is better; each has advantages and disadvantages. The research used a quantitative technique paradigm based on the positive approach principle. In particular, the quantitative technique is the most suited method for this study because most of the procedure involves quantifying and determining the impact of the constructs. The study employed a survey design using a scale to explore hypothesised correlations between variables while considering pre-existing knowledge about the phenomenon. Surveys are widely employed in research methodologies designed to collect data from a specific population or a population sample, and the survey instrument is a questionnaire (Robson, 1993).

A survey design is appropriate for obtaining a public opinion on social issues and societal realities relevant to the current state of phenomena and for establishing the natural context of existing circumstances in a state of affairs (Cresswell, 2009; Trochim, 2000; Cohen & Manion, 1980), and adopted for the current research in the adoption of online media as a Fatwa information platform among Malaysian Muslims. In social and behavioural sciences, the survey design is a superior method for collecting primary data, as it allows for direct observation of large sample size (Pope et al., 2002). It is a comparatively cheap and accurate method of getting information from respondents. Therefore, the survey method was selected because it is proven to be cost-effective and time-saving and allows an established method of data analysis that appeals to the researcher to deploy in research. Besides, the data is numerical and comes from accurate measurement; it can be checked for reliability and subjected to a critical analysis using the appropriate statistical methods (Neuman, 2014).

As a result, the main reason this study should be conducted using an online survey rather than an interview survey is that this research focuses on adopting online media. The target sample is those who use and interact with online media daily. Most study that evaluates online media adoption got respondents through online questionnaires. For example, Setyastuti et al. (2019) distributed an online questionnaire to the respondents via Facebook to know how social media is the preferred source of parenting among millennial moms or young mothers in Indonesia. Besides, Krystelle & Christian (2015), Okabe et al. (2021), Tan et al. (2022), and Scandurra et al. (2022) also used an online survey to get respondents in their research. In addition, this study was conducted when Malaysia was locked down due to the spread of the COVID-19 pandemic, making it risky to meet people face-to-face for data collection.

The present research explores whether Fatwa awareness, Maqāṣid al-Sharī'ah Application, Religiosity, and UTAUT2 influence the adoption of online media as a Fatwa information platform and how age, gender and education level moderate the relationship between these variables. Therefore, explanatory research has been used to understand the complex construct, cause, and effect between variables (Sobe &

Kowalczyk, 2013). Descriptive and causal analyses were used in this study (Hair et al., 2006). The descriptive analysis was performed using SPSS statistical analysis, while the interrelation of variables was using the Partial Least Squares Structural Equation Modeling Approach (PLS-SEM).

3.3 Research Process

Figure 3.1 below illustrates the seven-step quantitative research procedure used in this research, which was carried out following Neuman's (2014) approach.

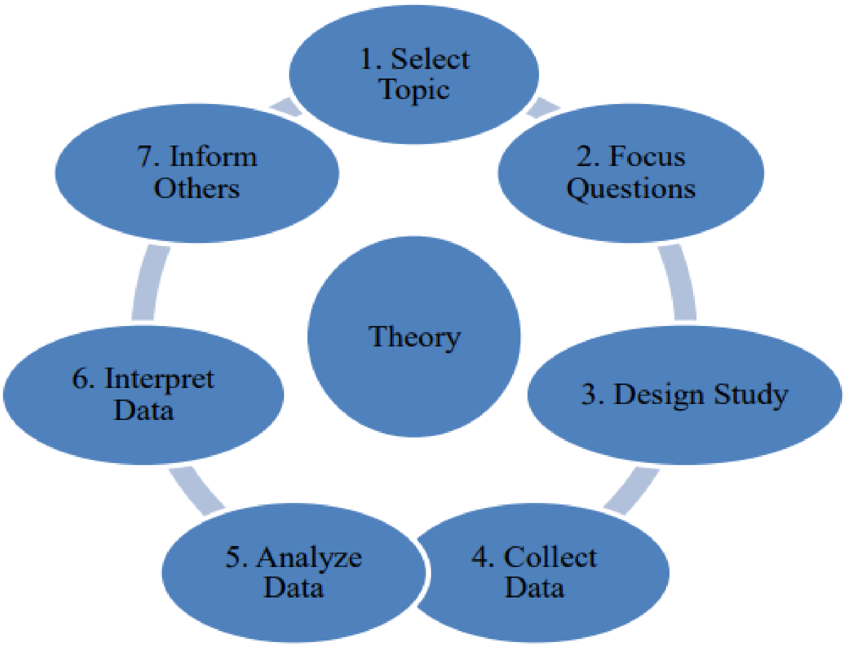


Figure 3-1: Steps in the Quantitative Research Process

The first step is to undertake a thorough literature review. The problem statement, research questions, and objectives will then be developed by identifying the gaps and problems in the literature while choosing the topic. The identified theories pertinent to the literature will serve as the foundation for establishing this research's theoretical framework and hypothesis. Among the fundamental theories selected for this study are (1) Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA), (2) Doll and Ajzen's (1992) Theory of Planned Behaviour (TPB), and (3) Davis' Technology Acceptance Model (TAM) (1989) (4) Venkatesh et al.'s (2003 & 2012) Unified Theory of Acceptance and Usage of Technology (UTAUT and UTAUT2).

An appropriate research design for the study will be established during the third step. A quantitative approach was employed in this study, primarily concerned with quantifying and identifying the data collection type. Fourthly, a set of questionnaires modified from prior studies will be utilized as the research instrument for the quantitative data-collecting technique in the measurement phase. This approach determined how Malaysian Muslims adopted online media as a Fatwa information platform. The questionnaire includes several demographic factor-related questions, such as age, gender, education level, and the Interval/Interval scale answer.

The questionnaires were distributed to Malaysian Muslims in the fifth and sixth stages. The data will then be examined. Outliers will be tested, and the general perspective of the responder will be analyzed. Measurement Model and Structural Model Assessment are carried out using Structured Equation Modelling (SEM) analysis.

3.4 Population and Sampling

The study's population consisted of Malaysian Muslims who used and interacted with online media daily using a convenience and snowball sampling technique.

3.4.1 The population of the study

The term "population" can describe the group of people, events, or things the researcher is interested in investigating (Sekaran, 2010). Another definition of the population is the theoretical concept of a sizable group of numerous cases from which a researcher selects a sample and to which sample results are extrapolated (Neuman, 2014). Even though several interpretations exist, the phrase's core stays the same. For example, if a vendor is interested in researching a customer's purchasing habits in Malaysia, the target population may be all consumers throughout the country. This study investigates the factors affecting Malaysian Muslim's adoption of online media in Malaysia. The study and investigation of adopting online media as a Fatwa information platform are still limited. Therefore, in this study, Malaysian Muslims will be selected as the population of the study or target population. It is important to investigate factors that affect their decision to adopt online media as a Fatwa information platform to improve Fatwa acceptance in Malaysia.

According to the latest DOSM (2010) statistics, around 17.4 million Muslims live in Malaysia. No latest official numbers exist for the number of Muslims in Malaysia. It is estimated that roughly 86% of the Malaysian population will be active online media users. This was a rise of 24% compared to 2016, in which online media users made up 62% of the overall population in Malaysia. Therefore, there are an estimated 14,964,000 Muslim online media users in Malaysia.

17,400,000 x 86% /100 = 14,964,000

3.4.2 Sampling method

According to Kothari (2004), a sample is a subset of the population studied in a research project. In contrast, sampling is the process of choosing a sufficient number of elements from the population so that the researcher can generalise specific properties or characteristics from the sample to the elements of the entire population. The probability and non-probability sampling approaches are the two main types of sample methods that researchers have extensively employed. In contrast to non-probability sampling, which is based on “non-random” selection, probability sampling is based on the concept of random selection.

A quantitative cross-sectional research technique will achieve the study’s goal (Bryman & Bell, 2015). Through social media platforms like Facebook, Telegram, and WhatsApp, primary data will be gathered through a web-based survey sent to a sample of internet users employing a non-probability sampling approach. This research employed convenience sampling, which is low-cost and straightforward to implement to reach a more extensive Malaysian resident base. In addition, this study adopted snowball sampling to obtain a reference from any survey participant by asking each personal and business contact to recommend other persons in their personal and professional network. Simultaneously, the researcher delivered online surveys to Facebook groups and communities in various districts throughout all Malaysian states. The combination of convenience and snowball sampling allows this study to reach a larger audience and increases the likelihood of engaging people with relevant knowledge and experience.

Convenience sampling, also known as an accidental or haphazard sample, is a non-probability sampling approach that employs individuals who may be researched conveniently (Beins & McCarthy, 2012). Although convenience sampling is the least generalizable and accurate sample methodology, there are occasions when there is no other option, such as when urgent information is required or when doing exploratory research. This type is rapid, easy, and less costly than other sampling methods.

3.4.3 Sample size

In selecting the sample size for this study, two factors must be considered: the population and the requirement to use a statistical tool of IBM-SPSS and SmartPLS. Krejcie and Morgan (1970) developed a table for simple reference to estimate the sample size for a given population. The formula for tabulating sample size is as follows.

$$s = X^2 NP (1 - P) \div d^2 (N - 1) + X^2 P (1 - P)$$

s = required sample size.

X^2 = the table value of chi-square for 1 degree of freedom at the

N = the population size.

P = the population proportion (assumed to be .50 since this would provide the maximum sample size)

d = the degree of accuracy expressed as a proportion (.05).

Table 3-2: Determining Sample Size for Research Activities, Educational and Psychological Measurement

N	S	N	S	N	S
10	10	600	234	25,000	378
20	19	700	248	50,000	381
30	28	800	260	75,000	382
50	44	1000	278	100,000	383
75	63	1200	291	250,000	384
100	80	1500	306	500,000	384
150	108	2000	322	1,000,000	384
200	132	2500	333	2,500,000	384
250	152	3500	346	10,000,000	384
300	169	5000	357	100,000,000	384
400	196	7500	365	200,000,000	384
500	217	10,000	370	300,000,000	384

N: Population size. S: Sample size. Confidence level= 95% with a 5% of error estimate.

Source: Krejcie and Morgan (1970)

Table 3-2 depicts the table for determining the sample size proposed by Krejcie and Morgan (1970). According to the latest DOSM (2010) statistics, around 17.4 million Muslims live in Malaysia. Therefore, Table 3-2 shows that 384 samples are required for populations 1,000,000 and above. As a result, the minimal sample size for the research based on the population is 384 respondents.

There are additional requirements because the research intends to employ the structural equation modelling (SEM) method. SEM's flexibility, which allows for the analysis of complex associations using numerous data types and comparisons between alternative models, is one of its strengths. However, these SEM characteristics also make it challenging to create general guidelines for sample size needs (MacCallum et al., 1999). Despite this, several rules of thumb have been proposed. For example, based on a ratio of indicators to latent variables as $r = p / k$, Boomsma (1985) suggested that $r = 4$ requires a sample size of at least 100 and $r = 2$ requires a 400 sample size. Roscoe (1975) proposes that sample sizes larger than 30 and less than 500 are appropriate for most research, and a minimum sample size of 30 for each category is necessary for samples to be broken into sub-samples; (males/females, young/adult).

Sample recommendations in PLS-SEM are also included because the current study employs it to analyse the data. PLS-SEM is a tool of the second generation that is fundamentally based on the characteristics of Ordinary Least Squares (OLS) regression. Cohen's (1992) rule of thumb states that measurement models must be acceptable in outer loadings (i.e., loading should be above the standard threshold of 0.70) based on his statistical power evaluations for multiple regression models. The minimum sample size requirements needed to detect any endogenous constructs in the structural model with minimum R^2 values of 0.10, 0.25, 0.50, and 0.75 for significance levels of 1%, 5%, and 10%, assuming the commonly used level of statistical power of 80% and a particular level of PLS path model complexity, defined as the maximum number of arrows pointing at a construct in the PLS path model.

Based on G-Power analysis, the study could gain an appropriate sample number. G Power analysis refers to obtaining a minimum number of samples for each analysis. Power can be understood as a chance that the test will detect a statistically significant difference or a relationship when such a difference or relationship exists. Power also refers to the probability of rejecting a null hypothesis. It is generally agreed that power should be .80 or greater; that is an 80% or bigger opportunity to find a statistically significant difference or relationship when there is one. Referring to G-power analysis, with an alpha value of .05 and a magnitude of the power of 0.95, the appropriate number of samples to run a path analysis is 153 respondents. A bigger sample size is not a problem, as Najib (1999) emphasized that a bigger sample size will strengthen reliability and validity.

3.4.4 Study locations

This study's data was collected throughout Malaysia. Table 3-3 shows that the states are divided into five zones. Each state was initially classified according to its zone, with Perlis, Kedah, and Pulau Pinang representing the Northern Zone, Selangor, Wilayah Putrajaya, Wilayah Kuala Lumpur representing the Central Zone, Kelantan, Terengganu, and Pahang representing the East Coast Zone, Negeri Sembilan, Melaka, and Johor representing the Southern Zone and Sabah, Sarawak and W.P. Labuan represent Sabah Sarawak. The researchers asked respondents to choose their zones and states before answering further questions. As Roscoe (1975) proposed, sample sizes must be larger than 30; thus, this research targets more than 30 respondents from each zone.

Table 3-3: Study Locations

Zone	States	Number of Respondents
Northern	Kedah Perlis Pulau Pinang Perak	>30
Central	Selangor W.P. Kuala Lumpur W.P. Putrajaya	>30
East Coast	Kelantan Terengganu Pahang	>30
Southern	Negeri Sembilan Melaka Johor	>30
Sabah/ Sarawak	Sabah Sarawak W.P. Labuan	>30

3.5 Research Instruments

The initial step in constructing the study's instrument was to identify previous research studies that addressed the same factors through the search of the journal and indexing databases such as Science Direct (http://www.sciencedirect.com/), Scopus (http://www.scopus.com/home.url), Taylor and Francis (http://www.taylorandfrancis.com/), Sagepub (http://www.sagepub.com/home.nav), Wiley (http://onlinelibrary.wiley.com/), Emerald (http://www.emeraldinsight.com/) and Google Scholars (https://scholar.google.com/). This research built the instrument based on prior research by Omar et al. (2012), Bolong et al. (2014), Osman et al. (2014), Venkatesh et al. (2003), Hu et al. (2003), Palis et al. (2006), Shaffril (2017), and Shamsudin (2018).

The second procedure was concerned with developing a construction definition for each variable. This may be accomplished most effectively by referencing previous research that has examined similar variables. The definitions of the variables evaluated in this research were adapted based on Venkatesh et al. (2003), Hu et al. (2003), Palis et al. (2006), and Shaffril et al. (2017). This definition provided the researcher with a further understanding of the variables studied. Second, reviewing ideas for the best technique to measure the variable resulted in new insights. Research studies conducted by Omar et al. (2012), Ramli et al. (2013), Bolong et al. (2014), Osman et al. (2014), Shaffril (2017), Shamsudin (2018), and Yahaya (2019) were adopted in this study. Information from these studies resulted in numerous suggestions for measuring the variables.

The instruments for this study were divided into four sections. After reviewing the literature, the questionnaire was constructed and modified via instrument development. The main goal of the instrument development process is to incorporate online media adoption items directly or indirectly related to online media adoption. This goal drives the present study to refer to the previous studies by der Heijden (2003), Worthington et al. (2003), Suki & Ramayah (2010), Davis (1989), Mokhlis (2009), Ramli et al. (2013), Bolong et al. (2014), Venkatesh et al. (2012), Osman et al. (2014), Shaffril (2017), and Shamsudin (2018) to construct the most appropriate items for the instrument. Then, an adopt and adapt methodology was used, in which items from previous research were altered to fit the current context of the study.

3.5.1 Section A (Respondent's demographic data)

The first section of the questionnaire is devoted to the respondents' demographic information. This section includes 11 questions about respondents' gender, race, age, residential area, educational achievement, occupation, monthly income, online media application and average time spent per day (hours). In this section, respondents were given closed-ended answers and were not permitted to pick more than one answer, except for question A8, which allowed respondents to choose more than one answer (Table 3-4).

Table 3-4: Instrument for Demographic Profile

No.	Measure	Items	References
A1	Location	(Open-ended)	This Research
A2	Gender	Male Female	Van der Heijden, (2003)
A3	Race	Malay Chinese Indian Other	Shaffril (2017)
A4	Age	Below 20 years old 21-30 years old 31-40 years old More than 41 years old	(Suki & Ramayah, 2010)
A5	Educational Level	Primary school Lower Certificate of Education (SRP/PMR/PT3) Malaysian Certificate of Education (SPM) Malaysian Higher Religious Certificate (STAM) Malaysian Higher School Certificate (STPM) Matriculation/ School of Foundation Studies Diploma Bachelor degree Master degree Doctorate of Philosophy (PhD) Others	(Suki & Ramayah, 2010)
A6	Occupation	Government sector Private sector	(Suki & Ramayah, 2010)

		Self-employed Student Pensioner Others	
A7	Monthly income	Below RM 2000 RM 2001 – RM 3500 RM 3501 – RM 5000 More than RM 5001 None	Hsu & Lin, (2008)
A8	Online media application	Facebook YouTube Twitter WhatsApp Blog Google+ Telegram Instagram Others	Shamsudin (2018)
A9	Average time on online media (Per day)	Less than 1 hour 1 – 2 hour 2 – 3 hour More than 3 hour	(Davis, 1989)

3.5.2 Section B (Fatwa Awareness)

Section B of the questionnaire focuses on respondents' Fatwa awareness. All questions are matrix questions with Likert scale answers of 1 (strongly disagree), 2 (disagree), 3 (not sure), 4 (agree), and 5 (strongly agree) were used to measure respondents' level of Fatwa awareness with items statements (Table 3-5).

Table 3-5: Instrument for Fatwa Awareness

Section	Number of Items/Statements	Item	Adapted and Modified from
Fatwa Awareness	14	B1-B14	Shamsudin (2018), Buang & Che Rosli (2018)

3.5.3 Section C (Behavioural factors studied)

Section C of the questionnaire focuses on the study's six behavioural variables and one mediating variable (CA, CB, CC, CD, CE, CF and CG), Performance expectancy, effort expectancy, social influence, habit, religiosity, Maqāṣid al-Sharī'ah Application and behavioural intentions. Four to six items represented each factor, and the total number of questions asked in section C was 35 (Table 3-6).

Table 3-6: Instruments for Behavioural factors studied

Section	Number of Items/Statements	Item	Adapted and Modified from
Performance expectancy	6	CA1-CA6	Venkatesh et al. (2012), Shaffril (2017)
Effort expectancy	5	CB1-CB2	Venkatesh et al. (2012), Shaffril (2017)
Social influence	4	CC1-CC2	Venkatesh et al. (2012), Shaffril (2017)
Habit	4	CD1-CD4	Venkatesh et al. (2012)
Religiosity	6	CE1-CE6	Worthington et al. (2003), Mokhlis, (2009)
Maqāṣid al-Sharī'ah Application	5	CF1-CF5	Alam et al. (2015), Abu Bakar et al. (2018)
Behavioural intentions	5	CG1-CG5	Venkatesh et al. (2012)

3.5.4 Section D (Online media adoption as a Fatwa information platform)

Section D of the questionnaire examines how Malaysian Muslims utilise online media to get Fatwa information. Six items represented the variable to evaluate respondents' level of online media adoption for Fatwa information. This section has five Likert scale response options ranging from 1 (hardly ever), 2 (rarely), 3 (sometimes), 4 (often), and 5 (always) (Table 3-7).

Table 3-7: Instrument for Online media adoption as a Fatwa information platform

Section D	Number of Items/Statements	Item	Adapted
Social media adoption as a Fatwa information platform	6	D1-D6	This research

3.6 Data Screening and Analysis

After the data collection process, the raw data goes through the data screening process to ensure that data is cleaned before embarking on the proposed statistical analyses. Figure 3-2 shows the flow chart of data screening and analysis.

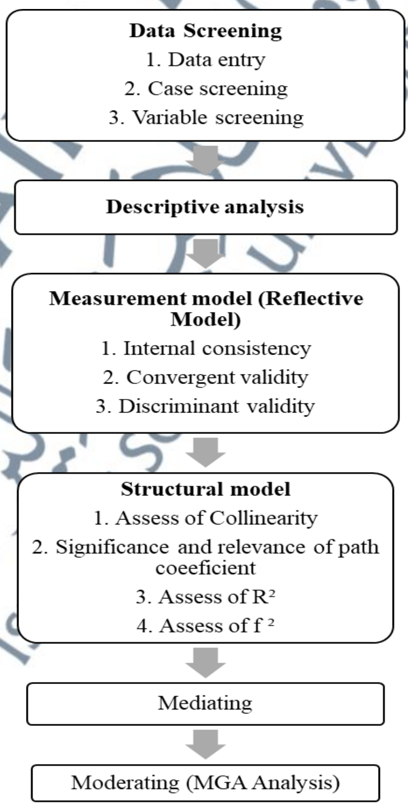


Figure 3-2: Data Screening and Analysis Step

3.7 Validity, Normality and Reliability

After developing an instrument set, testing its validity, normality, and reliability is essential. Validity is the process of ideas and measures conceptualization (Neuman, 2007). A data set's suitability for modelling by a normal distribution can be assessed using normality tests, which can also be used to estimate the likelihood that a random variable underlying the data set is normally distributed. While reliability is the level of consistency with which it measures whatever is measuring is achieved. This study had two validity and reliability processes; one was conducted before the data collection, and another was conducted after the data collection (Ary et al., 2002).

3.7.1 Validity

Neuman (2010) defines content validity as a "space" containing ideas and concepts; the measures should encompass all of the concepts' ideas or areas. There are two types of validity measurements: content validity and construct validity.

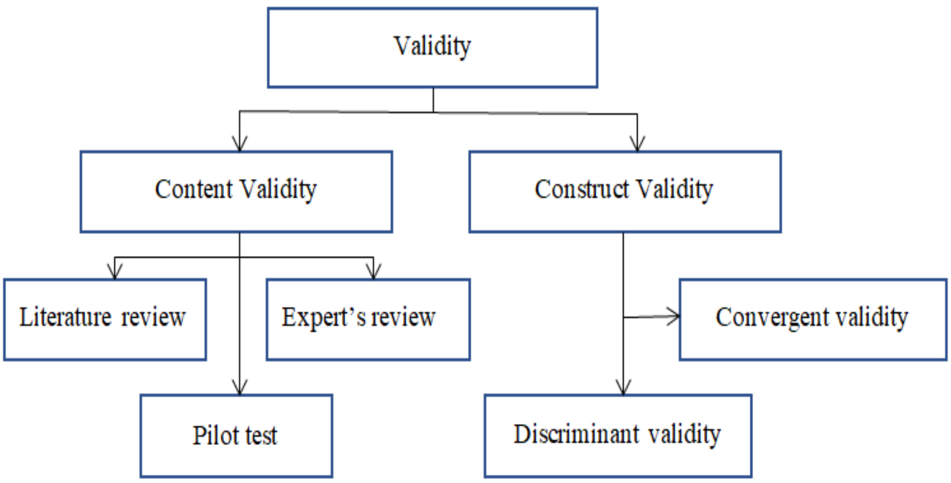


Figure 3-3: Method Used to Assess Validation Measures

Content validity entails three steps which thoroughly specify the entire content of a construct's definition, define a sample representative of all sections of the defined population, and develop an indicator that captures all of the definition's components. Content validation of an instrument always focuses on the material covered, the appropriateness of the wording in the questionnaire, and the adequacy of the sample of items to measure the construct (Ary et al., 2010). In this study, subject matter experts consist of the researcher's supervisory committee and four reviewer experts elected from different universities and fields to validate the questionnaire, including the clarity and readability of the items.

The first validator is Dr Abdul Manan Ismail, an Associate Professor in the Faculty of Syariah and Law, Universiti Sains Islam Malaysia (USIM), a Fatwa and Usul Fiqh expert. The second validator is Dr Shofian Ahmad, an Associate Professor in the Faculty of Islamic Studies, Universiti Kebangsaan Islam (UKM) and an expert in Syariah and Islamic research. The third validator is Dr Nik Ahmad Sufian bin Burhan @ Jaohari, a senior lecturer in the Faculty of Human Ecology, Universiti Pertanian Malaysia (UPM) and an expert in quantitative research and human behaviour. The last validator is Dr Mohd Sufiean Hassan Jaohari, a senior lecturer in the Faculty of Communication and Media Studies, Universiti Teknologi Mara (UITM), an expert in new media and communication.

3.7.2 Reliability

The term "reliability test" describes how consistently the same findings may be obtained from a measurement procedure, such as a test, observation, or questionnaire on repeated trials (Neuman, 2014). It may be summed up as the consistency or stability of scores throughout time or across raters. It is essential to understand that reliability relates more to scores than to specific individuals; therefore, considering someone as reliable in research is never acceptable. Generally, a pilot test is used to conduct the reliability test of a questionnaire.

A pilot test was conducted in Sungai Besi, Kuala Lumpur, where 30 respondents were involved in the pilot test process. As shown in Table 3-8, Cronbach alpha values for the pre-test were from 0.685-0.922, while for the actual study, the value was from 0.852-0.953. For both pilot and final tests, the Cronbach alpha value was within the appropriate values (above 0.7) Hair (2006) suggested.

Table 3-8: Reliability Coefficient for Pilot Test and Final Test

Variables	Pre-test (n=30)		Actual test (n=500)	
	No. Items	Alpha (α)	No. Items	Alpha (α)
Fatwa awareness	14	.721	14	.852
Performance expectancy	6	.706	6	.931
Effort expectancy	5	.922	5	.953
Social influence	4	.811	4	.883
Habit	4	.920	4	.938
Religiosity	6	.685	6	.875
Maqāṣid al-Sharī’ah Application	5	.854	5	.934
Behavioural intention	5	.919	5	.951
Adoption of online media as a Fatwa information Platform	6	.885	6	.931

3.7.3 Normality

A normality test has been conducted to assess the normality of the independent and dependent variable data with the accepted threshold. Table 3-9 shows the value of Kurtosis and Skewness for the independent and dependent variables. The kurtosis value was between -2 and +2, and skewness between -0.5 to 0.5 fit the criteria, as

George and Mallery (2010) showed. Thus, the distribution is approximately symmetrical.

Table 3-9: Assessment of Normality (n=500)

Variables	Min.	Max.	Mean	SD	Std.Error	Skewness	Kurtosis
Fatwa awareness	3.00	5.00	4.29	.504	.022	-.609	-.229
Performance expectancy	2.50	5.00	4.34	.667	.029	-.760	-.374
Effort expectancy	2.80	5.00	4.34	.682	.030	-.675	-.742
Social influence	1.50	5.00	3.91	.816	.036	-.412	-.408
Habit	1.00	5.00	3.93	.919	.041	-.674	.027
Religiosity	3.83	5.00	4.72	.339	.015	-1.17	.240
Maqāṣid al-Sharī'ah Application	1.00	5.00	3.96	.889	.039	-.535	-.408
Behavioural intention	2.00	5.00	4.19	.779	.035	-.663	-.458
Adoption of Online Media for Fatwa Information	2.00	5.00	4.14	.744	.033	-.555	-.472

3.8 Data Analysis

Statistical Package for the Social Science (SPSS) and Structural Equation Model Partial Least Square (SEM-PLS) was used to analyse the data. Descriptive analysis was performed using SPSS software. For descriptive analysis, frequency, percentage, mean and standard deviation were used to describe the demographic characteristics, level of Fatwa awareness, performance expectancy, effort expectancy, social influence, habit, religiosity, Maqāṣid al-Sharī'ah Application, behavioural intention and online media adoption. Because the present research consists of numerous latent variables and relationships among multiple predictors, Structural Equation Model Partial Least Square (SEM-PLS) is the analytical tool for quantitative data analysis. Researchers can use SEM to investigate a series of interrelated relationships between a set of constructs represented by numerous variables while accounting for measurement error. Brief descriptions of PLS-SEM, the justification for its application, the model's evaluation using measurement and structural models, and the issues with collinearity are given in the following subsections.

Table 3-10: Objective-based data analysis

No.	Objectives	Analysis
Objective 1	To obtain a profile on online media adoption as a Fatwa information platform among Malaysian Muslims.	Descriptive analysis (Frequency, percentage, mean and standard deviation)
Objective 2	To identify the level of Fatwa Awareness, Maqāṣid al-Sharī'ah Application, Religiosity, UTAUT2 behavioural factors, behavioural intention and online media adoption as a Fatwa information platform	Descriptive analysis (compute mean score divided into three categories: 1.00 to 2.399, 2.34 to 3.699 and 3.7 to 5.0 for low, medium and high, respectively
Objective 3	To determine the relationship between Fatwa Awareness, Maqāṣid al-Sharī'ah Application, Religiosity, UTAUT2 behavioural factors, behavioural intention and online media adoption as a Fatwa information platform	Structural Equation Modeling Using Partial Least Square (PLS-SEM)
Objective 4	To examine the mediating effect of behavioural intention on the relationship between Fatwa Awareness, Maqāṣid al-Sharī'ah Application, Religiosity, UTAUT2 behavioural factors and online media adoption as a Fatwa information platform	Structural Equation Modeling Using Partial Least Square (PLS-SEM)
Objective 5	To examine the moderating effect of age, gender and education level on the relationship between Fatwa Awareness, Maqāṣid al-Sharī'ah Application, Religiosity, UTAUT2 behavioural factors and behavioural intention of online media adoption as a Fatwa information platform	Structural Equation Modeling Using Partial Least Square (PLS-SEM)

3.8.1 Level of measurement

5 Likert scales are used for selected respondents to answer the question. The mean summated score was computed to gain the level of all the variables, resulting in a value ranging from 1 to 5. The mean score was grouped into three categories which were 1.00 to 2.399, 2.34 to 3.699, and 3.7 to 5.0 for low, medium, and high levels, respectively (Table 3-11).

Table 3-11: Level of measurement

Level	Mean score
Low	1.00 to 2.399
Moderate	2.40 to 3.699
High	3.7 to 5.0

3.8.2 Structural Equation Modeling Using Partial Least Square

The researcher used a Structural Equation Modeling Using Partial Least Square (PLS-SEM) to integrate the interdependencies between multiple variables. PLS-SEM is a multivariate technique consisting of latent and manifest variables. A latent variable is a variable that is not directly observed but inferred from a set of variables that we measure, including tests and surveys. Meanwhile, the manifest variable is described as an observed variable used to define the latent variables. When analysing a proposed theoretical model, PLS-SEM was used to evaluate how well it could estimate the covariance matrix for a sample dataset and its capacity to make sense of the variance in the endogenous variables. In PLS-SEM, independent and moderator variables represent exogenous variables, whilst dependent variables are endogenous. In this study, exogenous variables are behavioural factors, Fatwa awareness, religiosity, Maqāṣid al-Sharī'ah Application and behavioural intention variables, whereas the endogenous variable is online media adoption as a Fatwa information platform.

Partial least squares SEM (PLS-SEM) are an alternative to SEM (CB-SEM) co-variance, which defines its statistical properties. The purpose of employing PLS-SEM is to determine one or more key variables and identify the most important antecedents of the targeted variable (Hair et al., 2011). On the other hand, the model set-up should be a less developed theory which is a new or an extension of an existing theory (Hair et al., 2013; Henseler et al., 2009; Urbach & Ahleman, 2010). Besides, the data characteristics should have a small sample size, increasing the consistency of PLS-SEM estimations (Sarstedt et al., 2014). Therefore, since the researcher uses a less developed theory (extension of variables in existing theory), PLS-SEM analysis is used in this study.

3.8.3 Evaluation of PLS-SEM

A PLS path model comprises two elements: the measurement model and the structural model. The measurement model displays the relationship between latent variables and is placed at one level (without assigned exogenous and endogenous variables), while the structural model expresses the interrelationships between exogenous and endogenous variables. In summary, the measurement model studies measurement theory, whereas the structural model involves determining whether the structural relationship is significant and testing hypotheses.

3.8.4 Measurement Model

There are two types of measurement models: reflective and formative. The reflective measurement model is evaluated differently from the formative measurement model. The following subsections explain the measurement model for reflective construct and formative construct.

3.8.4.1 Reflective Measurement Model

Reflective measurement is treated as the outcomes of constructs. The variable is interchangeable (removed items without changing the meaning of the variable, have a measurement error, and items associated with a particular variable should be highly correlated with each other). On the other hand, the covariation among items is caused by and reflects variation in underlying latent factors (Jarvis et al., 2003). In the reflective measurement model, three criteria are needed at the outset. The criteria are internal consistency, convergent validity, and discriminant validity. These criteria are shown in Table 3-12 below.

Table 3-12: Reflective measurement model

Reflective Measurement Model	
Internal consistency	• Cronbach’s Alpha • Composite Reliability
Convergent validity	• Outer Loadings • Average Variance Extracted (AVE)
Discriminant validity	• Fornell & Larcker Criterion • Cross Loadings

The researcher investigates the indicator loadings in the reflective measuring model. The construct explains more than 50% of the indicator’s variance if the loadings exceed 0.70 (Sarstedt et al., 2014). The researcher then continues evaluating the constructions’ internal consistency and reliability. Composite reliability is frequently used in PLS-SEM to assess internal consistency reliability (Jo¨reskog’s, 1971). Higher values indicate a higher reliability level. Values between 0.70 and 0.95 are regarded as “satisfactory to good”, while the composite reliability values range between 0.60 and 0.70 as “acceptable in exploratory research” (Hair et al., 2014). Values greater than 0.95, on the other hand, are problematic because the items are duplicated, resulting in undesired response patterns, exaggerated correlations across indicators and error terms (Drolet & Morrison, 2001).

The reflecting measure’s convergent validity will be examined in the following phase. Convergent validity is the degree to which the individual item reflects a variable (Kline, 2011). It also acts as the internal consistency of a set of items and represents the strength of the relationship between the items predicted to represent a single variable (Brown, 2006). The characteristics of the items should represent only one factor and be strongly related to each other. Convergent validity can be tested using Average Variance Extracted (AVE) or factor loadings. An appropriate AVE is often 0.50 or higher since it indicates that, on average, the construct explains more than 50% of the variance of its elements (Bryne, 2010; Hair et al., 2010).

The next stage is to assess the discriminant validity of the constructs once the reliability and convergent validity of reflective constructs has been satisfactorily established. The degree to which a variable in the path model empirically differs from another is known as discriminant validity (Hair et al., 2010). The Fornell and Larcker (1981) criterion is considered the most conservative criterion for discriminant validity. This technique compares the AVE value of each construct to the squared inner construct correlation (a measure of shared variance) with all other constructs in the structural model. As a result, the recommended guideline is that a construct's shared variance with any other construct should not be higher than its AVE value. This approach is employed in the current study.

Studying the cross-loadings is a less exact approach to determining discriminant validity. As a rule of thumb, an indicator variable should be higher than the sum of its cross-loadings with other variables in the structural model (Hair et al., 2014). The construct shows discriminant validity if the indicators (items) loadings are consistently highest on the construct with which they are associated.

3.8.4.2 Formative Measurement Model

The assessment of the measurement model now moves on to constructs that are formatively assessed. As shown in Figure 3-4, the evaluation of formatively assessed constructs entails examining (1) convergent validity, (2) collinearity, and (3) statistical significance and the relevance of the indicator weights (Hair et al., 2014).

Hair et al. (2014) noted in Step 1 that the convergent validity of formatively measured constructs is determined by how the formatively measured construct correlates with a reflectively measured (or single-item) construct having the same meaning as the formatively measured construct. According to Hair et al. (2014), a path coefficient of about 0.80 indicates that the formatively measured construct should account for at least 65% of the reflectively measured item(s) variance.

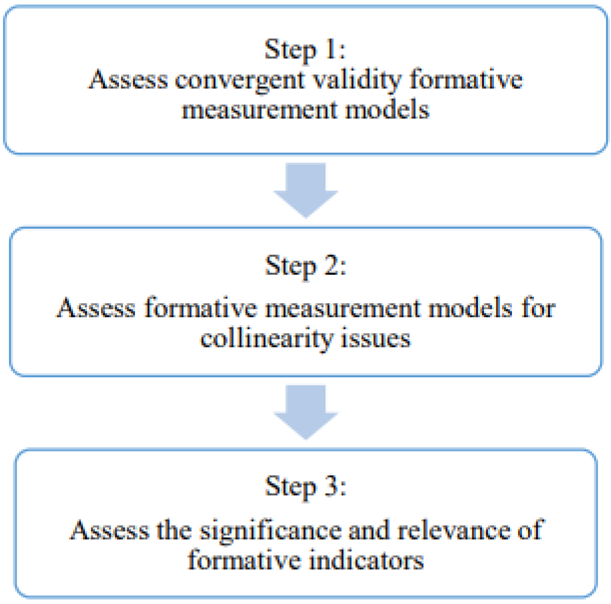


Figure 3-4: Formative Measurement Models Assessment Procedure

Source: Hair et al. (2014)

However, a path coefficient of 0.70 (corresponding to a shared variance of around 50%) would be acceptable in most circumstances. Thus, the final questionnaire must contain a single-item measure of the formatively measured construct or a reflectively evaluated construct for researchers to evaluate convergent validity during the research design stage. However, Hair et al. (2014) advised against avoiding using a single item for construct measurement. Diamantopoulos et al. (2012) state that single items have much lower predictive validity levels than multi-item scales, which might be problematic when using a variance-based analytic method like PLS-SEM. As previously mentioned, convergent validity assessment aims to have a measure that reflects the essence of the construct that the formative indicators are intended to measure (Sarstedt et al., 2012). Chin (1998) described redundancy analysis as using a formatively measured concept as an exogenous latent variable predicting an endogenous latent variable operationalized through one or more reflective measurements of the same construct.

Step 2 applies the variance inflation factor (VIF) to determine the level of collinearity between each item's formative indicators. Collinearity is the term used to describe situations with a high correlation between two formative indicators. The presence of more than two indicators is referred to as multicollinearity. Collinearity is commonly employed for the convenience of usage. The term “collinearity” is employed throughout the thesis and the subsequent discussion in the current study. From a methodological and interpreting perspective, collinearity problems might be problematic. Each indicator of the formatively assessed construct is regressed on all other measurement items of the same construct multiple times by the researcher. A VIF score of 5 or below in PLS-SEM is acceptable (Hair et al., 2011).

Step 3 evaluates the indicators’ significance and relevance. The indicators or error terms are not subject to any distributional assumptions in PLS-SEM, allowing for quick testing of the weights’ significance based on the normal distribution. For this reason, researchers must make a bootstrapping procedure, a resampling approach that creates many subsamples (usually 5000) from the original data (with replacement) and re-estimates the model for each subsample. The researcher can calculate standard bootstrap errors using these subsamples, allowing for the determination of *t* values (and p values) for each indicator weight. The importance of the weights may be assessed based on the *t* values to decide the following: The indication is retained if the weight has statistical significance. As long as theory and professional judgement justify its inclusion, an indicator is retained even if its weight is non-significant, but its loading is 0.50 or higher. If the weight is insignificant and the loading is low (i.e., less than 0.50), the indication should be removed from the measurement model.

Sarstedt et al. (2014) warned researchers not to delete formative indicators based on statistical outcomes for at least two reasons. First, the weight is a function of the number of indicators used to measure a construct. A higher number of indicators implies a lower average weight. In other words, formative measurement has an inherent limit on the number of indicators that can maintain a statistically significant weight. Secondly, removing formative indicators from the model should often be the exception since formative measurement theory requires measurements to cover a construct's entire domain. The content validity of the measurement model might be adversely affected by deleting an indicator (Hair et al., 2014). Indicator weights for relevance are standardised to values between -1 and +1, with weights closer to +1 denoting strong positive relationships and weights closer to -1 indicating strong negative relationships. The evaluation of PLS-SEM continues with the structural model assessment, which is covered in the next part once the measurement model assessment concludes that the model is satisfactory.

Regarding the guidelines in Figure 3.4 and the in-depth literature reviews in Chapter 2, Table 3-13 confirms and summarizes the measurement models adapted for the present research.

Table 3-13: Summary of decision for measurement models adapted for the present research

Constructs	Measurement model
Fatwa awareness	Reflective
Performance expectancy	Reflective
Effort expectancy	Reflective
Social influence	Reflective
Habit	Reflective
Religiosity	Reflective
Maqāṣid al-Sharī'ah Application	Reflective
Behavioural intention	Reflective
Online Media adoption for Fatwa information	Reflective

The evaluation of PLS-SEM then moves on to the measurement model assessment when the decision and justification of the measurement models are formed.

3.8.5 Structural Model Assessment

The structural model assessment begins when the measurement model assessment is completed and acceptable. The structural model assessment examines the independence of the relationships between the constructs proposed in the research model. Due to the lack of a common goodness-of-fit statistic, PLS-SEM differs from CB-SEM (Henseler & Sarstedt, 2013). Instead, PLS-SEM assessment of the model's quality is based on its ability to predict endogenous constructs. Figure 3-5 illustrates a systematical procedure for evaluating the output of structural models. In PLS-SEM, the significance of the path coefficients (Step 2), the level of R^2 value (Step 3), and the f^2 effect size (Step 4) are the main criteria for evaluating the structural model. Before this assessment, the researcher must examine the structural model for any predictor construct collinearity. Regression analyses are used to calculate the path coefficient connecting the constructs. So, the researcher must ensure that collinearity problems do not skew the regression results. The only difference between this phase and the formative measurement model assessment is that the scores of the exogenous latent variables are used as input for the VIF evaluations.

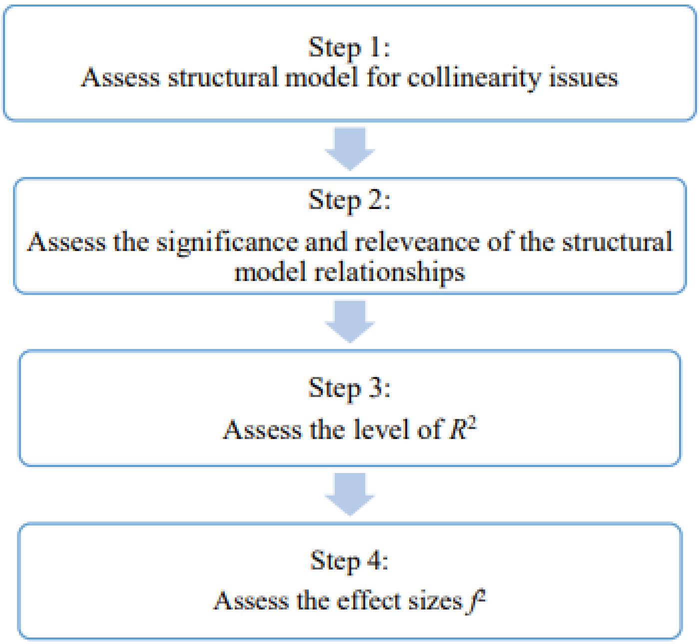


Figure 3-5: Structural Model Assessment Procedure

Step 2 assesses the significance and applicability of the structural model relationships (i.e., the path coefficients) that reflect the proposed relationships between the constructs. The significance assessment is based on bootstrapping standard errors to get the t values for the path coefficients, the same as the evaluation of formative indicator weights. Path coefficient values for relevance are normalised from -1 to +1, with coefficients closer to +1 suggesting strong positive relationships and coefficients closer to -1 indicating strong negative relationships. The study context must be taken into consideration when determining if the size of the coefficient is significant. The coefficient determination (R^2 value) is the most used measure for assessing the structural model in Step 3. R^2 measures the variation explained in each of the endogenous constructs, or put another way, it measures how accurately the model is predictive. Higher levels of the R^2, which goes from 0 to 1, indicate more prediction accuracy. R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively (Hair et al., 2011; Henseler et al., 2009). Nevertheless, the R^2 should always be interpreted in the context of the study by considering R2 values from related studies.

Step 4 involves measuring effect size f^2. The change in the R^2 value when a specific exogenous construct is removed from the model can be used to determine if the construct significantly influences the endogenous constructs, in addition to evaluating the R2 values of all endogenous constructs. The f^2 effect size is the name given to this metric. According to Cohen (1998), the exogenous latent variable's small, medium, and large effects are f^2 values of 0.02, 0.15, and 0.35. Last, while evaluating the relationships between exogenous and endogenous constructs in structural models, it is essential to include total effects, the sum of direct and indirect effects between the two constructs. Total effects are considered because it allows researchers to evaluate how an exogenous construct affects a target construct through all mediating constructs. This enhances understanding of the relationships in the structural model.

3.8.6 Mediation Analysis

In this study, the mediating impact analysis was examined. The mediating analysis includes establishing the indirect theoretical relationship between constructs to assess how indirect impacts change the hypothesised direct paths through the mediating variables. Hair et al. (2014; 2017) advised that researchers follow Hayes and Preacher's (2014; 2008) technique for assessing mediating effects and bootstrapping the sampling distribution of the indirect impact. According to Zhao et al. (2010) and Hayes (2009), bootstrapping is a nonparametric resampling procedure recognised as one of the most rigorous and robust ways to explore mediating effects. To explore the mediation impact of indirect effects that react to simple and numerous mediator models, Hair et al. (2014; 2017) enhanced the bootstrapping application. In addition, the bootstrapping method is ideal for PLS-SEM since it makes no assumptions about the variables' distribution or the statistics' sample distribution. This method is used in the present study to examine the mediating effects of the mediators, specifically behavioural intention, as described in Chapter 2. The findings of the behavioural intention mediation effects are stated in the following chapter.

3.8.7 Moderating Analysis

When the values of a variable that moderates the connection affect the impact of an external latent variable on an endogenous latent variable, this is known as the moderating effect. This is often referred to as an interacting impact. As a result, the PLS path model includes the interaction term as an auxiliary variable to consider the interaction between the moderator and exogenous latent variables. Moderators come in two types: categorical and continuous. The magnitude or direction of the relationship between an exogenous latent variable and an endogenous latent variable is affected by a continuous moderator. As mentioned by Henseler and Fassott (2010) and Henseler et al. (2016), to analyse the moderating effects, it is necessary to investigate the direct links between the exogenous and moderator variables and the interaction term with the endogenous variable. The significance of the path coefficient is evaluated using the bootstrap method. If the path coefficient is significant, then the moderating effect's magnitude must be evaluated. In the present study, the researcher intends to identify potential heterogeneity by analysing the moderating effect of gender, education level and age in the proposed relationships using multigroup analysis (MGA).

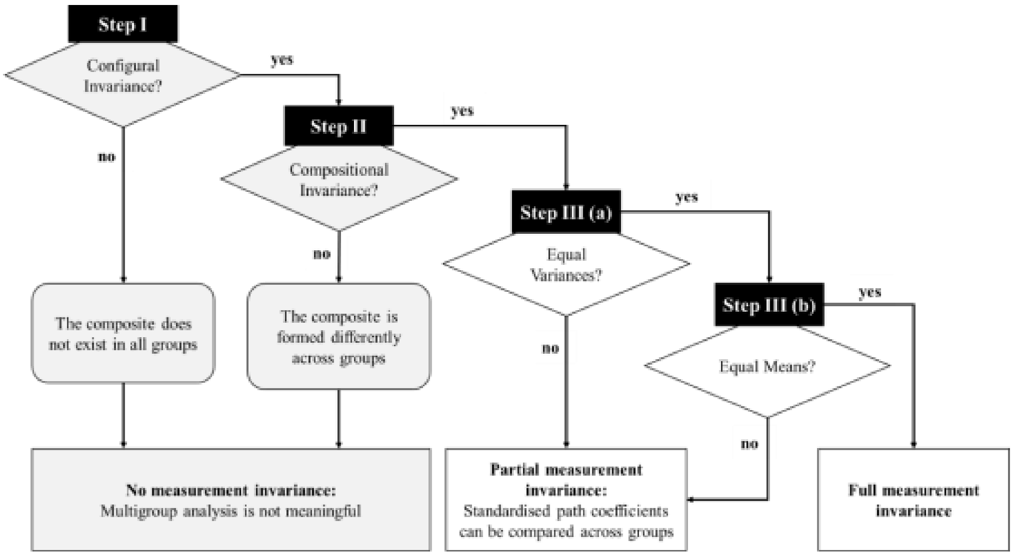
Many scholars have begun to investigate the concept of heterogeneity, in which market segmentation is based on differing views and assessments of products or services. Chin and Dibbern (2010) emphasized that disregarding heterogeneity frequently results in dubious conclusions. It is argued that studies that aggregate data as a single homogeneous population failed to determine whether there are substantial variations between two or more subgroups in the data. Multigroup analysis (MGA) is the suggested method for addressing this issue.

MGA or between-group analysis is a method for testing predetermined (also known as a priori) data groups to assess the existence of statistically significant variations between group-specific parameter estimations (e.g., outer weights, outer loadings, and path coefficients) (Hair et al., 2017). MGA enables researchers to test for differences between groups in two identical models when the groups are known.

According to Hair et al. (2017), MGA in PLSPM is among the most efficient methods for evaluating moderation across several connections. Standard moderation investigates a single structural link at the interaction point between the product of two exogenous variables and the endogenous variable (i.e., the dependent variable may be predicted by multiplying the independent variable by the moderator variable). In contrast, MGA provides a more thorough picture of the moderator's influence on the analysis outcomes, as the focus moves from assessing the moderator's effect on a single-modelled relationship to examining its effect on all modelled relationships (Hair et al., 2017, 2018).

Given that the basic assumption of MGA is group heterogeneity, it is beneficial for measuring group differences. According to Sarstedt and Ringle (2010), a researcher's failure to account for heterogeneity can jeopardize the validity of PLS-PM results, resulting in inaccurate conclusions. Assessing MGA in PLS-PM significantly improves researchers' capacity to find meaningful differences in numerous associations among group-specific data (PiconBerjoyo et al., 2016; Schlagel & Sarstedt, 2016). Following the recommendation of Henseler et al. (2016), the measurement models' acceptability and invariance must be determined before multigroup analysis is conducted. This study evaluated the measurement invariance of composites (MICOM) method using the measurement invariance method (Henseler et al., 2016).

The process consisted of three steps: i) the assessment of configurational invariance, ii) the assessment of compositional invariance, and iii) the assessment of equal means and variances. First, the configurational invariance was established due to the same assessment and adjustment of the measurement model for the gender, level of education and age group as was performed in the preceding phase. Second, the researcher conducted the permutation test using 500 permutations and a significance threshold of 5%. Thirdly, the researcher examined the composite mean values and variances for invariance. To clarify, composite invariance is obtained when the initial mean difference falls within the 95% confidence interval (Henseler et al., 2016).



Note: The boxes shaded in grey indicate that achievement of both configurational and compositional invariance are compulsory steps to proceed with the MGA technique

Figure 3-6: The Measurement Invariance of Composite Models (MICOM) Procedure

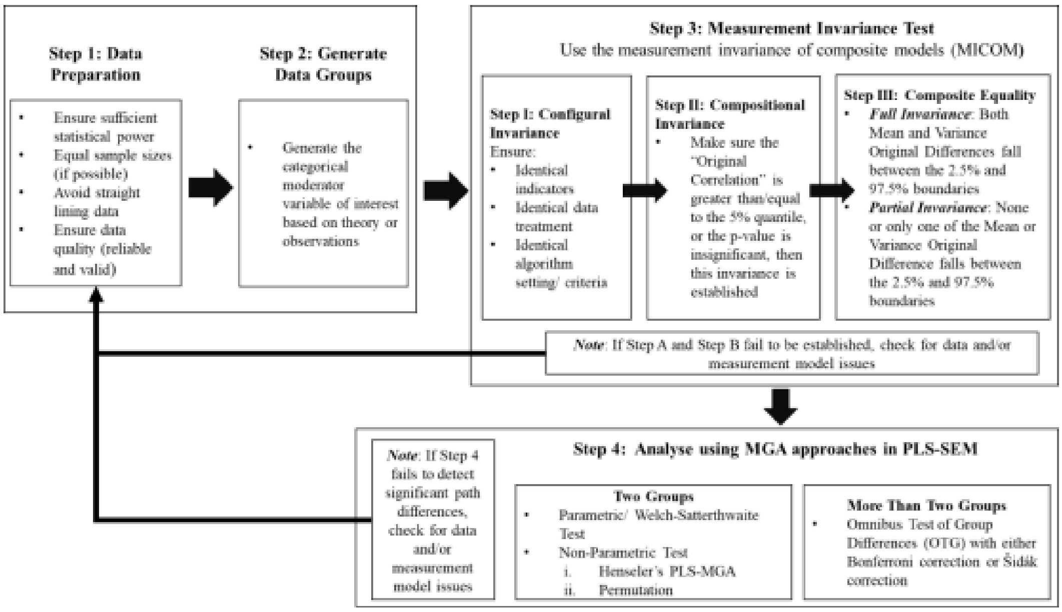


Figure 3-7: Guidelines for Running MGA in PLSPM

3.9 Conclusions

The present chapter focuses on the research design, the research instrument, the population and sample, the study location, validity and reliability before data collection, the data collection process, validity and reliability after data collection and data analysis. This study is quantitative (descriptive correlational study), where the developed questionnaire was used as the main instrument in collecting the required data. The research instrument has four main sections: respondent demographic data, Fatwa Awareness, behavioural factors studied and online media adoption as a Fatwa information platform.

The developed instrument has undergone two validity and reliability processes – before and after the data collection. The first stage of the instrument's validity relied on the literature review and experts and the reliability analysis that looked into the Cronbach alpha value of the pre-test process of each factor studied. Furthermore, the second validity and reliability of the instrument rely on the measurement and structural models. This study involved 500 Malaysian Muslims from five zones, where the number was gained based on convenience sampling and snowballing technique sampling. The survey was the primary technique used in collecting data. After completing the data collection process, the data were cleaned and analyzed using analysis software such as SPSS and SmartPLS.