CHAPTER III

RESEARCH METHODOLOGY

3.1 Research Paradigm

Paradigm can be interpreted as a concept, method, procedure, and rules collected into a framework that can be used in carrying out a study (Muslim, 2016). This study was conducted using a research paradigm with the type of Positivism. Positivism was generated from the thoughts of a French philosopher, Auguste Comte, who uses standardized laws and procedures as the basis so that science is considered deductive. This paradigm produced a quantitative approach (Muslim, 2016). This study will use a quantitative approach to gather and analyze quantitative data (numerical) followed by statistical analysis. Hence, the research design will be:

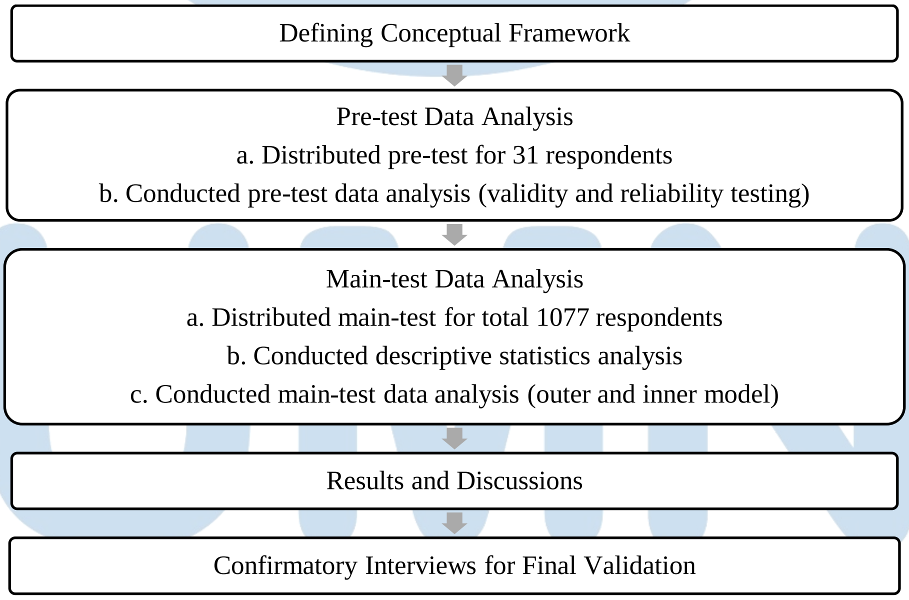

Figure 3.1 Research Design

At the end of the analysis of the results, there will be additional confirmatory interviews to give another validation for the main test data analysis that's been done before. There will be five respondents for these confirmatory interviews that will include:

Table 3.1 Confirmatory Respondents

No.	Role	Position	Number of Respondents
1.	Maker	Branch Operations Procedure, Head	1
2.	User	Regional Support and Supervision	3
3.	Controller	Operational Governance, Head	1

3.2 Research Object

This study was held in PT. MNO, one private bank in Indonesia on May 2021. This study involves all operational employees from all branches of PT. MNO across Indonesia that have been using Video Learning SOPs.

3.3 Population and Samples

3.3.1 Population

The population often associates with the number of people living in a specific country (Taherdoost, 2018). The population also refers to a generalization of subjects or objects with certain standards and characteristics which have been set by the researcher to be observed and to decide the conclusion (Sugiyono, 2017). Thus, the population in this study includes all employees of PT. MNO.

3.3.2 Samples

Samples are parts of the whole population that share the same characteristic as the population itself (Sugiyono, 2017). To set the samples of the study, a sampling frame needed to be determined. The sampling frame consists of real cases from which the sample will be extracted (Taherdoost, 2018). The sampling frame set in this study will include operational employees of PT. MNO. Determining samples also known as sampling is done by taking a subset from the selected sampling frame that will be applied to generalize the whole population (Taherdoost, 2018). The sampling process is affected by the sampling technique. This study will use the non-probability sampling technique, in more detail using the availability sampling technique.

The availability sampling technique is a non-probability sampling procedure where the population is selected from a targeted population connected to the research based on the availability (Daniel, 2012). In detail, this study will be utilizing the availability sampling technique. The allocation of samples used in this study was based on the selected elements and availability of the chosen segment. This approach helps the study receive more samples through the least time-consuming, simplest, and easiest implementation process (Daniel, 2012). The population will be taken from a selected segment of the operational team that works in all branches of PT. MNO across Indonesia. To detect minimum R^2 values of 0.1 for a significance level of 1%, the minimum sample number required is 158 (Hair et al., 2013). PT. MNO currently has approximately 2334 employees (as of July 2021) that belong to the operational team in all branches. The estimated respondents for this study are around 1000 respondents.

3.4 Variable Operationalization

Variable operationalization is used to define variables (including complex variables) clearly and objectively that will be utilized to examine hypotheses by using various tools to get fast and precise results (Sugiyono, 2018). Variables can be grouped into two groups: latent variables and indicator variables. Latent variables can be classified into endogenous or exogenous variables where exogenous latent variables act as independent variables and endogenous latent variables act as dependent variables (Hair et al., 2013).

In this study, there are four exogenous latent variables including: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Perceived Interactivity (PI); whereas there is only one endogenous latent variable which is Behavioural Intention (BI). Latent variables are not measured directly but represent and measured by several indicator variables indirectly (Beckett et al., 2017). Ergo, there will be five (5) latent variables and twenty-six (26) indicator variables as described in Table 3.2 below:

Table 3.2 Variable Operationalization

No	Variables	Definition	Indicator	Code	Measuring Scale
1.	Performance Expectancy (PE)	The extent to which users believe that applied technology will increase performances so they wish to use it continually (Venkatesh et al., 2012).	Improve understanding	PE1	Interval Scale 1 – 5 (1: very not agree - 5: very agree)
			Accelerate jobs	PE2	
			Increase efficiency	PE3	
			Simplify understanding	PE4	
			Increase productivity	PE5	
			Opportunity to developing	PE6	
2.	Effort Expectancy (EE)	The ease of using the technology will influence users to use it continually (Venkatesh et al., 2012).	Easy to learn	EE1	Interval Scale 1 – 5 (1: very not agree - 5: very agree)
			Easy to use	EE2	
			Clear and understandable	EE3	
			Easiness to be understood	EE4	
3.	Social Influence (SI)	The perception from important people to convince users to use the technology will influence users to use it continually (Venkatesh et al., 2012).	Influence from important people	SI1	Interval Scale 1 – 5 (1: very not agree - 5: very agree)
			Influence from influencing people	SI2	
			Management influence	SI3	
			Co-worker influence	SI4	

No	Variables	Definition	Indicator	Code	Measuring Scale
4.	Perceived Interactivity (PI)	The user's perception that interactions are two-way, controlled, and responsive to what they do (Willems et al., 2019)	Accessible anytime	PI1	Interval Scale 1 – 5 (1: very not agree - 5: very agree)
			Determine viewable content	PI2	
			Interact with other users	PI3	
			Relevance of information	PI4	
			Appropriateness of information	PI5	
			Suitability of information	PI6	
			Usefulness of information	PI7	
			Expected information	PI8	
5.	Behavioural Intention (BI)	Users desire to use the technology (Venkatesh et al., 2012).	Future intention	BI1	Interval Scale 1 – 5 (1: very not agree - 5: very agree)
			Making progress	BI2	
			Arranged for future program	BI3	
			Effective method	BI4	

Scales used in this study include interval scale, nominal scale and ordinal scale. An Interval scale shows the distance between one data and another with a constant range between each level of data to show characteristics or properties of the measured objects (Misbach, 2013). The nominal scale is a scale used to distinguish objects or events based on predicates and classify objects in the form of categories (Junaidi, 2015). The nominal scale in this study includes gender which will be divided into male and female options. The ordinal scale is used to set things in order without specific origins or operations. The ordinal scale in this study includes the year of birth from all samples. The questionnaire items related to variable operationalizations mentioned in Table 3.1 can be seen in Appendix A. Questionnaire Items.

3.5 Data Collection Technique

This study uses a questionnaire as a data collection technique for quantitative research. The questionnaire was distributed to sample respondents that have tried to and use Video Learning SOPs in PT. MNO. The questionnaire was made based on indicators shown in Table 3.1. The questionnaire also included several variables such as gender, age, and user profiles. This quantitative data is used as primary data for this study and the questionnaire will be distributed using Google Forms and analyzed using SPSS software version 22 and SMARTPLS 3.0 Program.

3.6 Data Analysis Technique

This study will cover descriptive statistics and inferential statistics. Descriptive statistics analyze data samples by providing descriptions or an overview without generalizations or conclusions (Sugiyono, 2018). Inferential statistics analyze data samples and their results using statistical techniques (Sugiyono, 2018).

The data analysis technique used is Structural Equation Model (SEM). SEM is an analysis technique used to examine a relationship series of dependent variables with a precise estimation through multiple regression equations that help researchers to include unobservable variables measured indirectly by indicator variables (Beckett et al., 2017; Hair et al., 2013). SEM can examine the relationship between one or more exogenous variables with one or more endogenous variables so the researcher will have a unifying framework.

There are two types of SEM: Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). CB-SEM is often used to confirm or reject theories where PLS-SEM is used to develop theories for explanatory research (Hair et al., 2013). PLS-SEM is also used to explain variance in the dependent variable, predict and explain key target constructs, and identify their relevance (Chin et al., 2020). By utilizing PLS-SEM, normality is not required, and it became one of its advantage (Hair et al., 2013). PLS-SEM enables researchers to estimate complex models that consist of many constructs, variables, and structural paths without inflicting with data distributional assumptions (Hair et al., 2019). Not just for explanatory research, PLS-SEM is also appropriate to be used in confirmatory research (Hair et al., 2017).

PLS-SEM should be considered for analysis that examines theoretical framework that derived from prediction perspectives; analysis with complex structural network consists of many constructs, indicators, and/or relationship model; analysis to have a better understanding through exploratory research for theory development; and for analysis that includes one or more formative constructs to be measured (Hair et al., 2019). PLS-SEM can also work on restricted sample size and work well for large sample size analysis (Hair et al., 2019). Therefore, this study that consists of many indicators through exploratory research is suitable for using PLS-SEM to explain the UTAUT model approach. Testing using PLS-SEM will require methods including:

a. Designing measurement model (Outer Model) analysis.

b. Designing structural model analysis (Inner Model) by performing causality test.

3.6.1 Descriptive Statistics

Descriptive statistics are used to describe sample data that can be measured by the mean, standard deviation, variance, maximum, minimum, sum, range, kurtosis, and the skewness of distribution (Ghozali, 2018). For each variable in this study, descriptive statistics will be used to generate the overall data frequency, mean, maximum, minimum, and median values. From all sample data collected in this study, descriptive statistics will be extracted using SMARTPLS 3.0 Program.

3.6.2 Pre-test Data Analysis

Pre-test data analysis used sample data from 31 random samples which have tried Video Learning SOPs in PT. MNO. All samples' data were processed with SPSS software version 22 to analyzed their validity and reliability.

a. Validity Testing

Validity testing is used to measure a set of items reflecting the theoretical latency in which the item is used to measure the latency. A higher validity value will give more validity to the study (Hair et al., 2013).

1) Pearson Correlation

Pearson Correlation coefficient measures a linear association between two continuous variables that show the statistical relationship strength (Obilor & Amadi, 2018). Variables' items proven to be valid when the value of Pearson Correlation > its actual value, or where the significance is > 0.5 (Hair et al., 2014).

2) Loading Factor of Component Matrix

The loading factor of Component Matrix measures the correlation between a variable and its factors (Malhotra et al., 2017). The study is considered accepted if the loading factor value is> 0.5 (Hair et al., 2014).

b. Reliability Testing

Reliability testing measures the extent to which latent variables are consistently related to one another. Reliability testing is conducted by measuring the value of Cronbach's Alpha, a conservative way of measuring reliability used widely by assessing the consistency of the entire scale (Ghozali, 2019; Hair et al., 2013). The study should have Cronbach's Alpha > 0.60 to be considered to have high reliability and it is recommended to have values 0.70-0.90 (Hair et al., 2019).

3.6.3 Main-test Data Analysis

3.6.3.1 Outer Model Analysis

Outer model analysis was conducted using SMARTPLS 3.0 Program by measuring validity and reliability values. Validity testing and reliability testing were carried out with the Outer Model to show how each indicator variable related to each latent variable (Hair et al., 2013).

a. Validity Testing

Validity testing is used to measure a set of items reflecting the theoretical latency in which the item is used to measure the latency. A higher validity value will give more validity to the study (Hair et al., 2013).

1) Convergent Validity

Convergent Validity is used to measure positive correlation with alternative measures of the same construct by measuring indicator reliability and average variance extracted (AVE) value (Hair et al., 2013). Indicator reliability is also commonly known as the size of outer loading. It is expected for each indicator to have an outer loading value > 0.70 (Hair et al., 2013). If sample data has a high outer loading value, it shows that the indicators of this study have a strong correlation to the construct. AVE value shows mean values for each latent variable in the reflective model. This study is expected to have an AVE value > 0.50 (Hair et al., 2013).

2) Discriminant Validity

Discriminant Validity measures whether a construct is truly perceptible from other constructs by empirical standards (Hair et al., 2013). Therefore, discriminant validity shows the uniqueness of a construct. There are two relied measurements of the discriminant validity, including cross-loadings and the Fornell-Larcker criterion. Cross-loadings are usually the first approach to measure discriminant validity. Specifically, an indicator's outer loading should have a greater value than any of its cross-loadings in another construct. The second approach of measuring discriminant validity is the Fornell-Larcker criterion by comparing the correlations of the latent variables with the square root of the AVE values. The AVE value is expected to be greater than the squared correlation with another construct (Hair et al., 2013). Another measurement that uses to determine the discriminant validity is the heterotrait-monotrait ratio (HTMT). HTMT shows the correlation between the trait and estimating the true correlation between two constructs. HTMT value should be < 1.0 (Hair et al., 2013).

b. Reliability Testing

Reliability testing measures the extent to which latent variables are consistently related to one another.

1) Composite Reliability

Composite reliability is a measurement used to measure the consistency of internal reliability. The study will have high reliability if it has a composite reliability value > 0.70 (Ghozali, 2019).

2) Cronbach's Alpha

Cronbach's Alpha is a conservative way of measuring reliability and is used widely by assessing the consistency of the entire scale (Ghozali, 2019; Hair et al., 2013). The study should have Cronbach's Alpha > 0.60 to be considered to have high reliability and it is recommended to have values 0.70 - 0.90 (Hair et al., 2019).

3.6.3.2 Structural Model Analysis (Inner Model)

Structural model analysis has three important metrics including: R^2 (explained variance), the statistical significance of the structural path coefficients, and f^2 (effect size) (Hair et al., 2013). Using SMARTPLS 3.0 in conducting the structural model analysis the research model used in this study is shown as below:

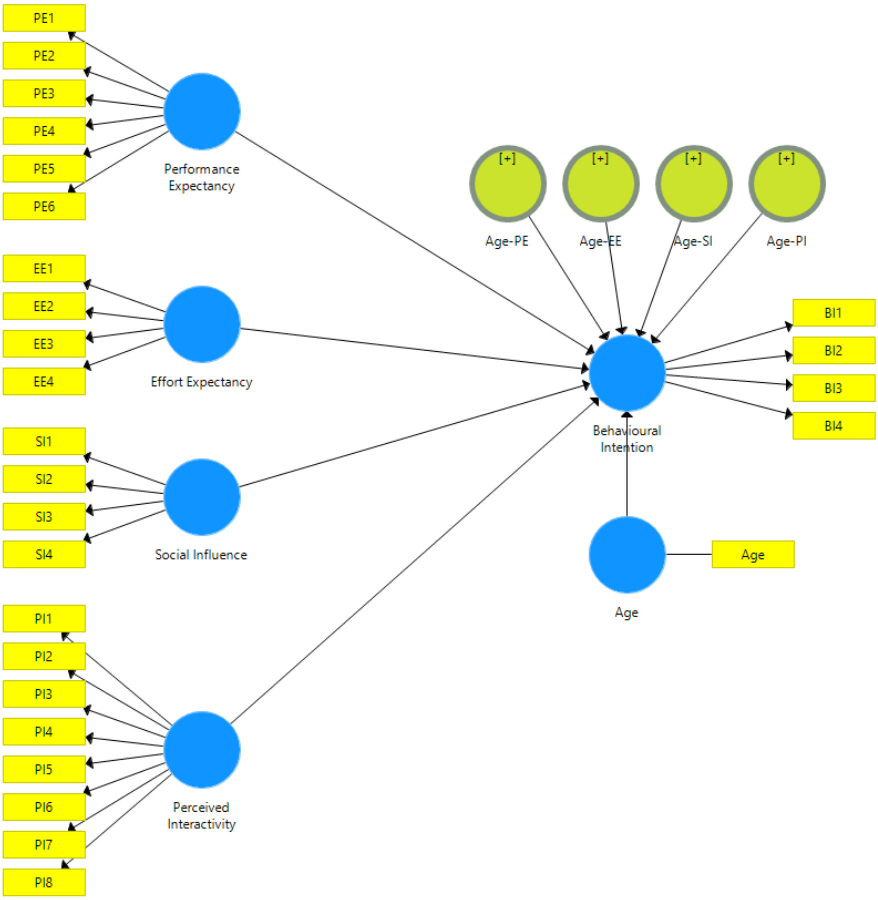

Figure 3.2 Research Model in SMARTPLS 3.0 Program
Source: Researcher (2021)

a. R^2 (explained variance)

R^2 also known as the coefficient of determination (Hair et al., 2013) representing the endogenous constructs variance explained by all related exogenous constructs. The range of R^2 varies from 0 to 1 and the higher value indicates a higher level of the prediction's accuracy. The expected R^2 results can be classified as substantial (0.75); moderate (0.50); and weak (0.25) (Hair et al., 2019).

b. Significancy Test – Hypothesis Test

Significancy test in PLS-SEM used to measure the effect of exogenous variables on endogenous variables by testing hypothesis using a bootstrapping procedure.

A bootstrapping procedure was used to measure the significance of path coefficient (Hair et al., 2013) and utilizing t-values on a two-tailed test. For a significance level of 10%, 5%, and 1% the critical t-values are 1.65, 1.96, and 2.57 (Hair et al., 2017). However, running bootstrapping procedure requires a minimum sample number at 5000 or at least as large as the number of valid observations. Rather than using the t-values, the significance test usually utilized p-values. P-values are used to assume a significant effect with no significance to determine the probability of rejecting the null hypothesis. Most researchers have a 5% significance level assumption, which means that a p-value smaller than 0.05 can be considered a significant relationship (Hair et al., 2013).

c. f^2 (effect size)

Complementing the measurement of R^2, the change in the R^2 values can be evaluated to determine whether a specific independent variable impact the dependent variable when it is omitted (Hair et al., 2013). The expected value of f^2 is classified into three categories: small effect (0.02); medium effect (0.15); and large effect (0.35).

3.7 Pre-Test Data Analysis Results

3.7.1 Validity Testing

The following are the results of the pre-test data analysis on validity testing (Pearson Correlation and Loading Factor) on 31 random samples which have used and tried Video Learning SOPs at PT. MNO:

Table 3.3 Validity Testing on Pre-test Data Analysis

No	Variables	Indicator	Pearson Correlation	Loading Factor	Validity
1.	Performance Expectancy (PE)	PE1	0.841	0.905	Valid
		PE2	0.915	0.940	Valid
		PE3	0.915	0.940	Valid
		PE4	**- 0.001**	**-0.273**	**Not Valid**
		PE5	0.820	0.786	Valid
		PE6	0.816	0.813	Valid

No	Variables	Indicator	Pearson Correlation	Loading Factor	Validity
2.	**Effort Expectancy (EE)**	EE1	0.837	0.727	Valid
		EE2	**0.096**	**-0.466**	**Not Valid**
		EE3	0.577	0.761	Valid
		EE4	0.834	0.854	Valid
3.	**Social Influence (SI)**	SI1	0.740	0.707	Valid
		SI2	0.758	0.817	Valid
		SI3	0.753	0.716	Valid
		SI4	0.683	0.703	Valid
4.	**Perceived Interactivity (PI)**	PI1	0.680	0.632	Valid
		PI2	0.700	0.667	Valid
		PI3	**0.498**	**0.386**	**Not Valid**
		PI4	**-0.292**	**-0.513**	**Not Valid**
		PI5	0.817	0.821	Valid
		PI6	0.880	0.931	Valid
		PI7	0.880	0.931	Valid
		PI8	0.762	0.795	Valid
5.	**Behavioural Intention (BI)**	BI1	0.990	0.991	Valid
		BI2	0.990	0.991	Valid
		BI3	0.902	0.897	Valid
		BI4	0.990	0.991	Valid

Source: SPSS software version 22 Analysis

Validity testing conducted on pre-test data analysis consist of two values, Pearson Correlation and Loading Factors. Both indicators require a value > 0.50 to be considered as valid indicators for each variable (Hair et al., 2014). As shown in Table 3.3, the pre-test data analysis found that 4 indicators are not valid. Those indicators are: PE4, EE2, PI3, and PI4. Those indicators have either the value of Pearson Correlation and Loading factors < 0.50. Those indicators failed to be proven to have a valid association to explain its variable well. Therefore, those indicators will be taken out from this study so those indicators won’t be analyzed in the main-test data analysis. Detailed data for validity testing on pre-test data can be seen in Appendix C and Appendix D.

3.7.2 Reliability Testing

The following are the results of the pre-test data analysis on reliability testing (Cronbach’s Alpha) conducted on 31 random samples of respondents who have used and tried Video Learning SOPs at PT. MNO by measuring the value of Cronbach’s Alpha:

Table 3.4 Reliability Testing on Pre-test Data Analysis

No	Variables	Cronbach's Alpha	Reliability
1.	Performance Expectancy (PE)	0.825	Reliable
2.	Effort Expectancy (EE)	0.740	Reliable
3.	Social Influence (SI)	0.697	Reliable
4.	Perceived Interactivity (PI)	0.810	Reliable
5.	Behavioural Intention (BI)	0.977	Reliable

Source: SPSS software version 22 Analysis

From the results above, this study shows that all variables have Cronbach's Alpha Value > 0.6. The result indicates that this study considered having high reliability (Hair et al., 2019). Therefore, through this reliability testing on pre-test data gathered from 31 random samples, we can conclude that all variables measured in this study are reliable and main-test data analysis can be carried out. Detailed data for reliability testing on pre-test data can be seen in Appendix E.