Chapter 3 Method and Procedures

This chapter discusses the research methods and procedures for this study. The Research "Onion" (Figure 3.1) proposed by Saunders et al. (2020) is the framework for discussing the research method. Therefore, this chapter discusses research philosophies, approaches to theory development, research strategies, and data collection and analysis procedures. The data collection and analysis procedures encompass the design of the questionnaire instruments, sampling techniques, statistical and qualitative data analysis methods, and the ethical issues of this study.

3.1. The Research Philosophy

Research philosophy is a way to examine, understand and explain a social phenomenon (M. Saunders et al., 2016). There are three types of research philosophies: (1) positivism, (2) interpretivism, and (3) realism (Polonsky & Waller, 2018; Saunders et al., 2020; Sekaran & Bougie, 2019).

3.1.1. Positivism

Positivism posits that researchers are separated from the research subject (Weber, 2004) and have very little influence (M Saunders et al., 2016). Hence, researchers need to be objective throughout the research process (Merriam, 1998). As a common practice, researchers adopting a positivist approach tend to use deductive reasoning quantitative studies (Cavana et al., 2001; M. Saunders et al., 2016). Deductive reasoning is about forming several hypotheses, stating those hypotheses into operational terms, collecting relevant quantitative data, and using statistical analysis to test them (Malhotra, 2009; Malhotra et al., 2004). Several statistical analysis methods were applied to identify the association and relationship between and among the variables under study. Such work intend to start the second round of data collection after the first round. Therefore, it is a cross-sectional study.

Second, this study adopts both questionnaire survey and case study. A questionnaire survey is advantageous because of the efficiency of collecting large amount of numerical data (Saunders et al., 2020; Sekaran & Bougie, 2019). On the other hand, a questionnaire survey is easy to administer. Thus, it offers an efficient and effective means of collecting many people's opinions or behavioral patterns.

However, a questionnaire survey is limited by its depth and understanding of the perspectives of the respondents. Survey only collects quantitative data based on the structured, measurable items in the questionnaire. It does not allow researchers to know more about the reason behind such a choice (D. R. Cooper & P. S. Schindler, 2014). This limitation has to be supplemented by the case study methodology.

The case study strategy is a strategy that looks into the current phenomenon in real-life using many data collection methods (Yin, 2013). Collis and Hussey (2013) identify six case study types as shown in Table 3-1.

Table 3-1 Six Types of Case Study

Case study type	Purpose/nature
Exploratory case study	It is conducted where there are few theories, or the body of knowledge is deficient
Opportunist case study	It is conducted due to the researchers' access to a specific business, group, or individuals.
Descriptive case study	It aims at describing current practices.
Illustrative case study	It aims at illustrating a new practice adopted by an

case study were analyzed through thematic analysis (Braun & Clarke, 2012). There are five stages in thematic analysis. The first stage is about familiarizing with the data of the 29 semi-structured interviews. The second stage is about searching for themes and sub-themes through reading the interview scripts. It involves discovering the patterns within the interview scripts. The third stage is about reviewing the potential themes and sub-themes and ensuring their quality for them. It involves asking questions about the quality of the themes and whether there are sufficient, relevant, and meaningful data supporting the themes and sub-themes. The fourth stage is about defining and naming the themes. Finally, it involves a thorough analysis of the contents within each theme and sub-theme. There are normally two types of themes: (1) descriptive and (2) conceptual and interpretative themes. The last stage is to produce the report (Braun & Clarke, 2012).

3.3.4. Pilot Study

Two pilot surveys were conducted to refine and validate the items of the measure. A small group of post-graduate students did the first survey at middle management with experience of exerting and receiving transformational-instructor leadership. They were asked to comment on the use of word, the length of research instrument, the format of questionnaire, and the relevance of contexts. Finally, the survey instrument was revised to consider the comment and feedback obtained from the two pilot tests.

3.4. Statistical Data Analysis

Lowry and Gaskin (2014) state there are two generations of statistical techniques. The first generation uses the method of multiple regressions, correlation coefficient and methods of comparing the means such as T-test and ANOVA. These methods are suitable demonstrated, previous researchers only tested the relationship between TIL and the four student outcomes without the mediation of IM and EM (see Chapter 2). Therefore, PLS-SEM, which is primarily exploratory, is more suitable than CB-SEM, primarily confirmatory.

Overall, PLS-SEM has the following advantages: (if) capable of handling research model that is complex with little research data, (ii) able to estimate normatively specified measurement models, and (iii) produce determinate latent variable scores (Sarstedt et al., 2020). In short, SEM must be applied in this study since the model has a complex relationship between one independent variable to two mediators and four dependent variables.

The major data analysis technique for PLS-SEM in accepting or rejecting the hypotheses is path analysis. Path analysis refers to a statistical approach for examining the link between two or more variables. PLS-SEM is a subset of it. It is a more sophisticated analytic approach than multiple regression analysis since it allows for examining the connection between one or more independent variables and a single dependent variable. However, path analysis enables the examination of the connections between many independent factors and multiple dependent variables or mediators. Thus, researchers have greater creative freedom in designing the study model (Hair et al., 2017). This study employs path analysis due to one independent factor, several mediators, and four dependent variables. As a result, such a study is only possible when using path analysis in PLS-SEM. In the path analysis, coefficient of determination (R^2), size and significance of path coefficients, f^2 effect sizes, and q^2 effective size are analyzed to determine the robustness of the path relationship.

Chapter 4 Data Analysis and Discussion

This chapter starts with the demographic characteristics of respondents. It then proceeds to the first type of analysis and path analysis. It then ends with the mean and standard deviation analysis and one-way ANOVA analysis. Each discussion of analysis starts with the nature and rationale for each analysis. There are three types of data analyses in this chapter. The first one is the tests for the validity and reliability of the analyzed research model. They include indicator validity and exploratory factor analysis for the construct validity, Cronbach's Alpha and composite reliability for internal consistency reliability, the correlation coefficient for discriminant validity, and multicollinearity analysis. The second one is the path analysis which indicates which hypotheses were accepted or rejected. The third one is basic data analyses such as demographic characteristics of the respondents, mean and standard deviation analysis, and one-way ANOVA analysis.

4.3. Validity and Reliability of Instruments for Measuring Constructs

It is crucial to discuss the concept of validity and reliability after discussing the demographic characteristics. In statistics and research studies, the validity of instruments refers to whether a research instrument measures what it is supposed to measure (i.e., a research construct) (D. Cooper & P. S. Schindler, 2014). Therefore, validity means whether various indicators in a questionnaire or other instruments measure a construct (Hair et al., 2017). In other words, in a questionnaire, there are many indicators for a construct. Therefore, an indicator must be representing the nature of a construct. Reliability of instruments refers to how reliable a research instrument is in measuring the research construct (D. Cooper & P. S. Schindler, 2014). Therefore, reliability means whether the various indicators accurately measure a construct (Hair et al., 2017). Graphical representation as extracted in Hair et al. (2017) is shown in Figure 4-2.

know whether one scale correlates with another measurement scale. If the correlation between the one scale and another scale is high, the scale has *convergent validity*. *Discriminant validity* refers to the degree to which scores on a scale do not correlate with scores from scales designed to measure different constructs (D. Cooper & P. S. Schindler, 2014). In other words, there are many sub-scales in measuring different constructs in a questionnaire instrument, it is crucial whether measurement of a construct such as "perceived academic performance" is not correlated with the measurement of another construct such as "affective learning." If the correlation between the two scales is not high, the two scales have discriminant validity.

In terms of measuring convergent validity, an ideal way is to calculate the correlation of a proposed test for a construct with an established one (D. Cooper & P. S. Schindler, 2014). However, it is not always possible since an instrument for a construct may be the first of a kind. It means that there may not be a competing instrument for measuring the correlation of the instrument with a competing one. Alternatively, PLS-SEM applies *outer loadings* and the *average variance extracted (AVE)* to determine the convergent validity (D. Cooper & P. S. Schindler, 2014).

First, the *outer loading* analysis uses the logic that a measurable construct item is an alternative approach to measure the same construct. The measurable item has convergent validity if the measurable item covers or shares a high proportion of variance of the construct. In other words, outer loading is measured by dividing the amount of variance captured by an indicator by the amount of total variance of a construct (Hair et al., 2017). In other words, outer loading represents the amount of variation of an item explained by the construct (i.e., measured by the total variance of the construct). An

4.3.2. Reliability of instruments

Reliability is a measurement of how accurate a scale for measuring a construct is. The most common measure is internal consistency reliability using Cronbach's Alpha. Cronbach's Alpha measures how closely related a set of items are as a group (Ott & Longnecker, 2015). Cronbach's Alpha is acceptable at .70, good at .80 and excellent at .90. Cronbach's Alpha **internal consistency reliability** measure and **composite reliability (CR)** are used to measure reliability in PLS-SEM. **Composite reliability** considers the different outer loadings of the indicators. It is calculated by summing the outer loadings of indicators and dividing them by the sum of itself and the variance of the measurement errors (Hair et al., 2017). It is a better measure than Cronbach's Alpha since it is not sensitive to the number of items in the scale. CR of .60 to .70 is acceptable in exploratory research. For more advanced stages of research, the value between .70 and .90 are considered satisfactory. The above .90 is not desirable because they indicate that all indicators are measuring the same thing, rendering it meaningless (Hair et al., 2017).

4.3.3. Multicollinearity and Model Fit

Multicollinearity is a statistical phenomenon in which one predictor variable in a path model can be predicted linearly from the others with a substantial degree of accuracy. It indicates that, even though the criteria for validity and reliability are satisfied, one predictor can still be predicted linearly by another predictor. It indicates that the quality of the data collected may be problematic. Multicollinearity is measured by a variance inflation factor (VIF) (Hair et al., 2017). The formula of VIF is shown below:

adjusted R Square as the final R Square calculation(Ott & Longnecker, 2015). A high R Square means more of the variances of a construct is predicted by another construct. TIL has the highest R Square to PAP and IM in this study, followed by IC, CL, EM, and AL. All R Square measurements are statistically significant.

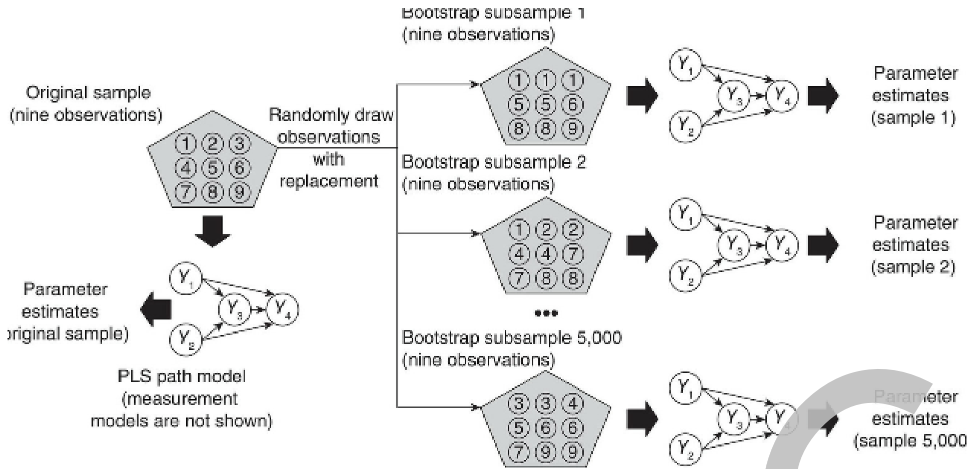
An associated measurement of R Square is **F Square or effect size**. Effect size determines the level of influence on another construct once the former construct is removed from the calculation. For example, the following formula calculates it:

$$F\ Square = \frac{(R\ Square\ included - \text{R Square excluded})}{(1 - R\ Square\ included)}$$

In the above formula, R Square included is the R Square that encompasses the influence of a construct on another construct. In contrast, R Square excluded is the R Square that excludes the influence of the subject construct to another construct.

A higher level of F Square indicates a higher level of predictive accuracy. According to Cohen (1988), .02, .15, and .35 indicate small, medium, and large effect sizes. Per Table 4-8, the effect size of TIL->IM is the largest at 1.112, followed by EM at .491. It means that IM and EM have large effects on the influence of TIL on other constructs. It is normal since TIL is the only independent variable and both IM and EM are the mediators. In other words, only through IM and EM can TIL influence the other four constructs or outcomes.

As for the rest of them, the effect sizes of IM to CL and PAP are moderately large and large, respectively. Besides, the significant effect size of IM to AL is slightly lower than the medium threshold suggested by Cohen (1988). On the other hand, none of the F Square from EM is statistically significant, indicating that EM does not influence the change of R Square or coefficient of determination of any of the four outcomes. In other



Source: Hair et al. (2017)

Therefore, to estimate the t-value or p-value, bootstrapping is a technique that is needed to generate as many random samples as possible. In other words, making the data pattern more random is necessary to estimate the t or p-value.

In this study, as recommended by Hair et al. (2017), 5,000 bootstrap samples, each of which includes the same number of cases as the number of observations in the original data set, are drawn to arrive at the significance level. Table 4-10 shows that TIL is statistically significant to all two mediators and the four outcomes. On the other hand, one of the mediators---IM is statistically significant to three outcomes: AL, CL, and PAP. However, another mediator-EM is only statistically significant to IC. The path effect of EM to IC is also much smaller than that of IM. Judging only by the p-value estimation, IM seems to be a much stronger mediator than EM.

R Square is also known as the coefficient of determination. It determines how well a construct is explained by another construct (Ott & Longnecker, 2015). It is calculated by the square of the correlation coefficient or r. Researchers often use the