BAB III
RESEARCH METHODOLOGY

3.1 Research Object General Descriptions

The writer has objectives while working on this dissertation. The goal is to analyse the impact of Supply chain risk resilience on Supply Chain Disruptions, IT Resilience, and Big Data Analytics.

Supply chain risk resilience is from the words Supply chain and Risk Resilience. Supply Chain itself means supply chain seems to be more common across peers to peers than the definition of supply chain management. (Cooper and Ellram 1993; La Londe and Masters 1994; Lambert, Stock, and Ellram 1998; Mentzer, DeWitt, Keebler, Min, Nix, Smith, and Zacharia 2001). Another definition of the supply chain is a network of organizations that involves, throughout up and downstream leakages, the difference between processes and activities that produce valuable forms of products and services delivered to the ultimate consumer (Christopher 1992; Mentzer, DeWitt, Keebler, Min, Nix, Smith, and Zacharia 2001) Issues, and facets concerning in between this dissertation. As well the supply chain, the boundaries of SCM, the antecedents, and the consequences were already discussed. Historically, supply chain management has several definitions, and it is believed possible to develop a single, encompassing definition of SCM. The early stages of AI involvement in supply chain management focused on utilizing AI tools for inventory management, demand forecasting, risk management, and sustainable supply chain management. Organizations primarily use AI methods for better decision-making in these areas. However, there was a lack of understanding of how AI could lead to capability building at the supply chain level, and many organizations faced barriers in leveraging AI technologies effectively (Merhkdot Pournader 2021)

Based on the description, the questionnaire object that will be used is those who are experienced in supply chain management and AI. With a minimum of working experience in both fields of 2 years, and since this research will benefit more people in Indonesia and ASEAN, I decided to distribute the questionnaire across several ASEAN countries, including Malaysia, Thailand, Philippines, Vietnam, and Singapore. The reasons behind choosing this country are:

- Rapid Economic Growth: These countries are experiencing significant economic growth, with a growing middle class and increasing demand for consumer goods. This translates to a rapidly evolving and complex supply chain landscape, making them prime targets for research on future trends. (data.worldbank.org/2024)

- Tech Adoption: Southeast Asia is witnessing a surge in technology adoption across industries, including advancements in big data analytics crucial for supply chain risk management and resilience. My research can explore how these countries are leveraging big data for supply chain improvements. (asean.org/2022)

- Vulnerability to Disruptions: The region is prone to natural disasters and geopolitical tensions, making supply chains susceptible to disruptions. My questionnaire can investigate how these countries are preparing for and mitigating future disruptions through big data and risk management strategies.
(worldbank.org/2023)

- Government Initiatives: Many Southeast Asian governments are actively promoting supply chain development and digitalization. Understanding how government policies are shaping the future of supply chains in these countries can be valuable to my research.

- Diverse Economies: While these countries share some characteristics, their economies are not identical. Surveying companies across these nations can provide insights into how different industry structures and economic landscapes influence approaches to big data and risk resilience in supply chains.

- Language: English is widely spoken in business circles across these countries, making it easier for me to administer my questionnaire and obtain a wider range of responses.

- Accessibility: These countries are generally accessible to researchers, with good travel connections and a growing research infrastructure.

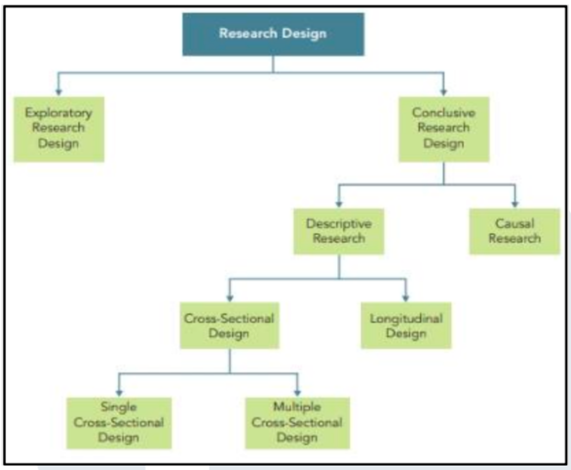
To gather the most relevant data, I'll be targeting individuals with expertise in supply chain management, big data, and risk mitigation. Their insights are crucial for my research on the future of Southeast Asian supply chains. I'll also be reaching out to these individuals to help spread the word to others in their network who share this expertise. However, to ensure the accuracy of my findings, only responses from qualified individuals will be included in the final analysis.

3.2 Research Design

In marketing research, a research design acts like a detailed roadmap. It lays out the specific steps and procedures needed to tackle research questions and solve problems effectively (Malhotra, 2019).

3.2.1 Type of Research

From Malhotra's (2019) point of view, there are two types of research, there are:



Picture 3.1 Research Design

Source: Malhotra, (2019).

3.2.1.1 Exploratory Research Design

Exploratory Research Design is a type of research that can help gain comprehension and discover information about existing problems or situations. This research method has an unstructured and adaptable nature, allowing for flexibility in the research process (Malhotra, 2019)

3.2.1.2 Conclusive Research Design

Conclusive research designs are used to test specific ideas (hypotheses) and identify relationships between variables (correlations) in marketing research (Malhotra, 2019). Malhotra et al. (2017) further categorize conclusive research designs into two main types:

a. Descriptive Research

Agreeing with Malhotra et al., (2017), clearly inquiries about maybe a strategy in inquiring about a plan that can portray something, inquire about utilizing this strategy is carried out in an organised way, and incorporates a particular theory. So, in collecting the data required to conduct inquiries about it has been clarified clearly. Clear inquiry comprises two sorts, specifically:

i. Cross-sectional design

Cross-sectional design is a method to gather data in a period that has been determined with only done with one sample from populations. Cross-sectional itself is divided into two types, namely:

1. Single cross-sectional designs could be a test obtained from 1 respondent from a foreordained target populace and information data obtained from a test of respondents as it were once.
2. Multiple cross-sectional designs is a test obtained from 2 or more foreordained target populace respondents, and information data is obtained from the test as it were once.

ii. Longitudinal design.

Longitudinal design obtains data more than once in a period that has been determined using a fixed sample.

b. Casual Research

Casual research is a sampling method that is used to identify if there are connections between cause and effect.

During the identification process, I used conclusive research with descriptive research method because my objection is to study and analyse the impacts on supply chain risk resilience towards Supply chain disruptions, IT Resilience, and big data analytics. Using a single cross-sectional design to obtain data, where a single cross-sectional design is a way to collect only once each respondent. Based on the main journal that I used as a reference using a Likert scale of 1 to 5, because the journal gave that it has significant connections between Supply chain risk resilience, I use a Likert scale from 1 to 5. There is nothing to change to adapt.

3.3 Populations and Samples

3.3.1 Populations

In research, a population refers to the entire group of individuals or objects that share specific characteristics relevant to the study. The researcher defines these characteristics to ensure the conclusions drawn are representative of the whole group (Sugiyono, 2013). Another way to think of a population is as a collection of elements that meet the same criteria established by the researcher (Malhotra et al., 2017).

3.3.2 Sample

The test could be a subgroup of the populace or a portion that can speak to the populace (Malhotra et al., 2017; Sugiyono, 2013). In deciding the test to be utilized in inquiry, there are inspecting methods that can be utilised to consider the test (Malhotra et al., 2017). Concurring to Malhotra et al., (2017), testing strategies comprise of 2 sorts, to be specific:

A. Probability Sampling

Carrying out this sampling, samples will be taken randomly, making it possible to measure estimates from the sample in describing the desired criteria.

B. Non-probability Sampling

When conducting non-probability testing, examining is based on the author's subjective point of see and isn't based on propensities in selecting test components. The creator decides characteristics of criteria in selecting and taking non-probability tests. Methods for non-probability testing comprise of 4 sorts, to be specific:

i. Convenience Sampling

Convenience sampling is a way to generate samples by convenience while the writer is at the right time, conditions, and place. This technique is easier to access, graded, and more cooperative.

ii. Judgmental Sampling

Judgmental sampling is a technique for generating a sample that is slightly similar to convenience sampling, but the criteria and terms are slightly more than convenience sampling.

iii. Quota Sampling

Quota sampling is a method of picking a sample based on the composition of specified populations that are on the selected criteria

iv. Snowball Sampling

Snowball sampling is a way to generate samples randomly, but the individuals who participate are mandated to follow the criteria based on the characteristics that are needed in the research. Next, everyone who is finished with the survey is requested to find another person who has similar criteria to be the next participant.

While doing this research, I used non-probability sampling with a judgmental sampling technique and snowball sampling to collect the sample. It ought to do so because of the specific criteria that I need, so it correlated with my topic of research. Because of that, several respondent criteria are listed below:

1. Respondent's domicile is in an ASEAN country (Indonesia, Malaysia, Singapore, Philippines, Vietnam, and Thailand) other than that, as long as ASEAN is accepted.
2. The respondent's minimum age is 21 years old.
3. The respondent has been working with their company for a minimum of 1 years.
4. The respondent needed to have experience working in the supply chain and IT field in an area wherever the office is. This can be in healthcare, manufacturing, logistics, Services (hotel/restaurant), or even IT services.

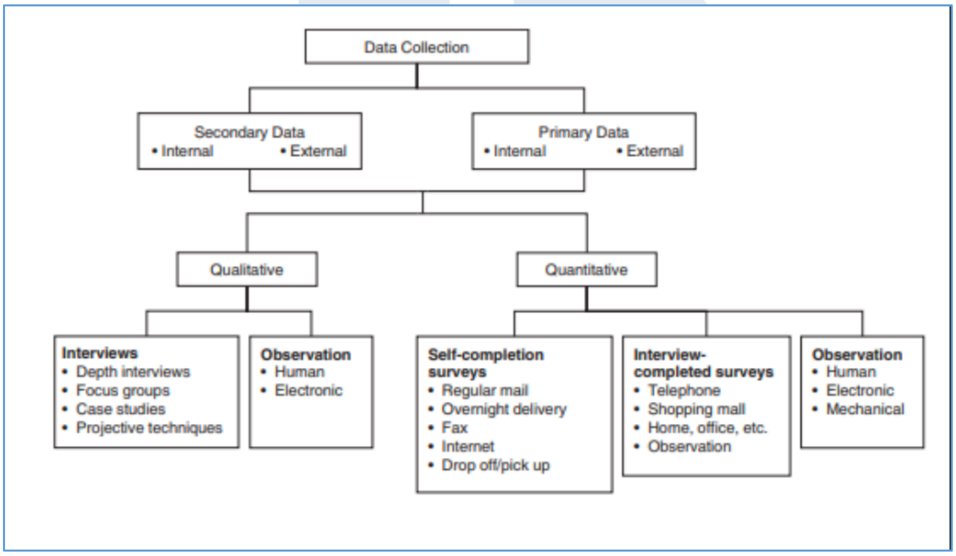
   If any respondents do not meet the requirements that have been set, the respondent data can't proceed further.

3.3.3 Sampling size

In deciding the test estimate, some components must be considered simultaneously (Hair et al., 2019). Because of this, deciding the proper test estimate could be a complicated matter since subjective and quantitative contemplations are required in arrange to discover an adjustment point for the existing components (Malhotra, 2019; Hair et al., 2019). Concurring to Hair et al. (2021) in deciding or deciding the number of tests to be utilised in inquiry, the creator alludes to the equation n x 5 (number of pointers utilised multiplied by 5).

So based on the equation over, in conducting this inquiry, the creator will test four factors with the entire number of pointers utilised being 22. In deciding the least number of tests required in this inquiry about utilising the equation 22 x 5 = 110, the least number of tests is 110 respondents.

3.4 Data Collecting Technique



Picture 3.2Data Collecting Technique

Source: Hair et al. (2019)

Hair et al., (2019) say there are two types of research data, namely:

3.4.1 Primary Data

Primary Data Primary data is information gathered firsthand by the researcher to address the research question. This data can be collected through various methods, such as surveys, interviews, or focus group discussions (FGDs).

3.4.2 Secondary Data

Secondary data refers to information gathered and utilized in past research to address problem formulation (Hair et al., 2019). The selection of the type and quantity of data collection is determined by the research design and objectives, according to Hair et al. (2019). The two categories of data collection techniques are:

3.4.3 Qualitative Data Collection

Qualitative data collection would be more appropriate for use in exploratory research designs Because it aims to provide understanding regarding the occurrence of a phenomenon. Qualitative data collection consists of 2 general approaches, namely observation and interviews.

3.4.4 Quantitative Data Collection

Quantitative data collection is ideal for conclusive research designs, whether they aim to describe a phenomenon (descriptive) or establish cause-and-effect relationships (causal) (Malhotra et al., 2019). This is because conclusive research typically involves well-defined research questions that lend themselves well to collecting numerical data. There are three main categories of quantitative data collection techniques:

1. Self-completion surveys:
   This category uses a questionnaire with questions that have been designed to collect data from respondents. Respondents can complete this questionnaire independently, online or offline.
2. Interviewer-completed surveys:
   This category is like a self-completion survey, which.
   The difference is that filling is done directly, whether through communication using chat, telephone, or face-to-face.
3. Observation
   Observations that are done are mostly done online using digital devices.

During this study, the author has collected primary data using quantitative methods, specifically through the distribution of questionnaires or surveys. To promote the use of secondary data in this research, the author has also utilised information from previous research, websites, and scientific books. The following outlines the author's data collection process for this research:

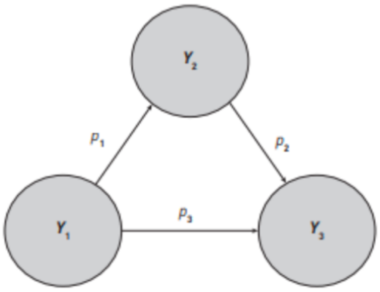
A. Look up, gather, and select secondary data to be a supporting research data that are collected from many websites, research articles, and books.
B. While working on this research, the main journal is also the reference for creating this journal.
C. I created the questions for the survey and created the questionnaire using a digital questionnaire, Microsoft Forms.
D. My research requires no pre-test due to all of the indicators based on the journal reference are validated already.
E. I gathered up to 137 questionnaire respondents by sharing the questionnaire link with all colleagues.
F. Works on the data that has been collected with a minimum of 110 respondents using application as the media; the application is SmartPLS4.

3.5 Research Variable Identifications

3.5.1 Endogen Variable

In research models, endogenous constructs are like the dependent variable but are measured using multiple questions or indicators. These indicators are derived from the model itself and are influenced by other constructs within the model (Malhotra & Birks, 2017). In this research, the variable that plays a role as an endogen variable is Supply Chain Risk Resilience (SCRR).

3.5.2 Mediation Variable



Picture 3.3 Mediation Variable

Source: Hair et al., (2022)

Mediation takes place when a mediator variable acts as a third construct that influences the relationship between two correlated constructs (Hair et al., 2022). This means that a change in the initial construct impacts the mediator variable, which then leads to alterations in the final construct in the PLS path model. Essentially, the mediator variable shapes the process behind the correlation between the two constructs. The exploration of mediation effects has a key prerequisite, which is substantial theoretical support. If such a correlation is present, mediation can serve as a valuable statistical analysis method, provided that the correct steps are taken (Hair et al., 2022).

Mediation involves two types of relationships: direct effects and indirect effects. Direct effects refer to correlations that exist between two constructs and are represented by a single arrow path. On the other hand, indirect effects involve correlations that consist of multiple series of relationships, with at least one intervening construct involved (Hair et al., 2022).

According to Hair et al., (2017), there are two types of effects in non-mediation, namely:

1. Direct-only nonmedication, which has a significant direct effect but not an indirect effect.

2. No-effect nonmedication, not significant in direct and indirect effects.

According to Zhao et al. in Hair et al (2017), there are three.

Types of mediation, namely:

1. Complementary mediation, direct effect, and indirect effect

immediately produce significance and show direction.

Similar.

2. Composite mediation, direct effects, and indirect effects

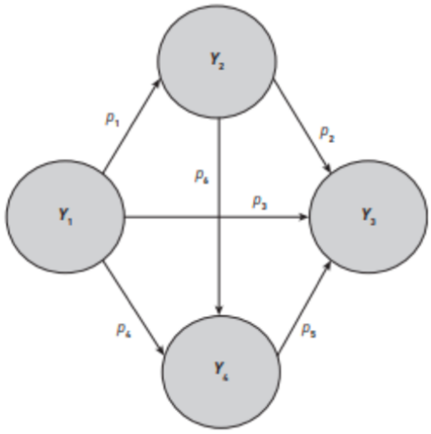
directly produce significant results but show the direction.

Of the opposite.

3. Indirect-only mediation, the direct effect is not significant,

but the indirect effect was significant.

3.5.3 Multiple Mediation Variable



Picture 3.4 Multiple Mediation Variable

Source: Hair et al., (2022)

In research models using Partial Least Squares Structural Equation Modeling (PLS-SEM), it's common to encounter situations where a single independent variable (estrogen construct) might influence multiple mediating variables simultaneously. In such cases, relying on separate mediation analyses for each mediator can be misleading (Cepeda Carrión et al., in Hair et al., 2022). There are two main reasons why separate mediation analyses are discouraged by Preacher and Hayes (in Hair et al., 2022):

1. Inaccurate Indirect Effects: Summing indirect effects from separate analyses wouldn't provide an accurate picture of the total indirect effect. This is because the mediating variables are likely to be correlated with each other.
2. Misleading Hypothesis Testing: Confidence intervals and hypothesis tests for indirect effects in separate analyses can be inaccurate if they don't account for the presence of other potential mediators.

Therefore, researchers are recommended to include all relevant mediating variables in a single PLS-SEM model to gain a complete understanding of how independent variables influence dependent variables through these mediating factors (Sarstedt et al., Hair et al., 2022). This approach allows for a more comprehensive analysis of the hypothesised relationships. Multiple mediation analysis allows researchers to explore different types of mediation effects within a single model. Following the approach outlined by Zhao et al. (Hair et al., 2022), this research will assess the significance of both indirect and direct effects using bootstrapping procedures in SmartPLS.

My research uses mediation variables because my research only has one mediation variable, which is Big Data Analytics.

3.5.4 Exogenous Variable

In research models, exogenous constructs act like independent variables in traditional statistical tests but are measured with multiple questions or indicators. These constructs represent external factors influencing the model and aren't explained by other variables within the model itself (Malhotra & Birks, 2017). In this dissertation, there are 2 Exogenous variables, which are Institutional Response to SCD (IRSCD) and IT Infrastructure Capabilities (ITIC).

3.6 Variable Operationalization

Variable operationalization plays a big role in deciding and measuring scares from the variable that has been used for research and solving the problems that the writer has found. This research investigates the impact of several factors on supply chain risk resilience. The key variables examined are:

- Supply Chain Disruption: This refers to unexpected events that can interrupt the flow of goods and services within a supply chain.
- IT Resilience: These variables measure the ability of information technology systems to adapt to and recover from disruptions.
- Big Data Analytics: This captures the use of advanced data analysis techniques to gain insights and improve decision-making related to supply chain risks.
- Supply Chain Risk Resilience: This is the overall ability of a supply chain to withstand and recover from disruptions.

The study employs a 5-point Likert scale for data collection. On this scale, five represents "strongly agree", and one signifies "strongly disagree."

Table 3.1 Operational Variable

No	Variable	Definition of Variable	Code	Measurement	Scaling Technique	Reference
1.	Institutional Response to Supply Chain Disruption	Institutional response to supply chain disruption (ISCD) can be defined as the organization's ability to develop strategies based on previous experience with supply chain disruption events to effectively deal with disruptions from various sources such as logistics failures,	ISCD1	Based on previous experience with supply chain disruption events, our firm develops strategies to deal with disruption from logistics failures such as transportation failures, condition of roads, and fleet utilization.	5 Scale Likert	
			ISCD2	Based on previous experience with supply chain		

		natural disasters, and man-made disasters		disruption events, our firm develops strategies to deal with disruption from natural disasters such as floods, earthquakes and droughts.		
			ISC D3	Based on previous experience with supply chain disruption events, our firm develops strategies to deal with disruption from man-made disasters such as labor strikes, terrorism, sabotage, hacking, fire, government		

				policy change, etc.		
2.	IT infrastructure capability	IT Infrastructure Capability (ITIC) can be defined as the organization's ability to utilize its technological, managerial, and technical IT resources to perform its business activities, including physical IT infrastructure and IT managers' business and technical skills	ITIC 1	Our firm uses IT-based systems in identifying potential threats to our supply chain from internal and external environments	5 Scale Likert	
			ITIC 2	Our firm uses IT-based systems to identify and	5 Scale Likert	

				assess risk within supply chain		
			ITIC 3	Our firm uses IT-based systems for Risk treatment in our supply chain. (Developing a range of options for mitigating the risk, assessing those options, and then preparing and implementing action plans.)	5 Scale Likert	
			ITIC 4	Our firm uses IT-based systems for continual monitoring and review of risks and their treatment within our supply chain	5 Scale Likert	

3.	Big Data Analytics Capbility	Big Data Analytics is the organization's ability to collect, mine, analyze, and visualize data effectively, enabling decision-makers to develop actionable intelligence for decision-making. Additionally, BDA capabilities within an organization enable it to process complex calculations, perform pattern analysis, customize	BDA 1	Our firm invests in big data analytics software (e.g. SAS Enterprise Miner, Tableau)	5 Scale Likert	

		product offerings, improve transparency, and accountability.				
			BDA 2	Our firm invests in processes which ensure availability of high-quality and timely data for employees	5 Scale Likert	
			BDA 3	Our firm currently utilizes some form of distributed file systems (e.g. Hadoop Distributed File Systems (HDFS))	5 Scale Likert	
			BDA 4	Our firm currently utilizes some form of	5 Scale Likert	

				distributed database systems (e.g. NoSQL or Cassandra)		
			BDA 5	Our firm has taken initiatives to increase pool of individuals skilled in big data analytics	5 Scale Likert	
			BDA 6	Our firm encourages employees to leverage their big data analytics skills to solve problems	5 Scale Likert	
			BDA 7	Our firm has managerial resources to take relevant actions on insights derived from big data analytics	5 Scale Likert	

			BDA 8	Our firm incentivizes employees to get certified in big data analytics technologies	5 Scale Likert	
			BDA 9	Our firm's top management encourages employee to come up with innovative big data initiatives	5 Scale Likert	
			BDA 10	Our firm focuses on forging strategic contacts with analytics knowledge leaders in the field	5 Scale Likert	
			BDA 11	Our firm invests in documenting processes and procedures for big data analytics	5 Scale Likert	

			BDA 12	Our firm invests in knowledge management systems	5 Scale Likert	
4.	Risk resilience	Risk Resilience can be defined as the organization's ability to respond quickly, recover faster, or develop innovative ways of doing business under duress compared to others. It is seen as a desirable characteristic for an organization to possess in order to deal	RES 1	Our firm has resources to get ready during crisis	5 Scale Likert	

		with various types of adversity				
			RES 2	Our firm can respond quickly to disruptions	5 Scale Likert	
			RES 3	Our firm is able to adapt to the supply chain/business process disruption easily	5 Scale Likert	
			RES 4	Our firm is able to maintain business continuity even after a supply chain/business process disruption event	5 Scale Likert	
			RES 5	Our firm gets recovery from a disruption event in short time	5 Scale Likert	

			RES 6	Our firm's ability to handle crisis reduces the impact of business loss	5 Scale Likert	

3.7 Data Analysis Technique

3.7.1 Pre-Test

The pre-test that we're talking about here is about trial using 10% to 25% of respondents from the questionnaire or survey that has been distributed, it is to identify and minimize if there are problems that we don't want to happen in the middle of running data (Malhotra & Burgess, 2020). The total of the pre-test sample on this research in total is 40 respondent with Microsoft Form.

3.7.2 Validity and Reliability Test

3.7.2.1 Validity Test

Validity testing is a crucial step in research. It ensures that the measurements used accurately capture the characteristics of the phenomenon being studied (Malhotra & Burgess, 2020). In this research, the author relies on SmartPLS 4 software to process questionnaire data and assess the validity of each indicator within the measurement model. Validity testing itself involves applying various criteria to evaluate the measurement model. A table outlining these specific criteria will be presented next to illustrate further the process used in this research.

Table 3.2 Validity Test

No.	Size Validity	Definition	Required Value	
1.	Matrix Component: Factor Loadings	According to Hair et al. (2019), factor loadings are a representation of the correlation between the original variables and the derived factors.	Valid, if the value of factor loadings >0,7	Invalid if the value of factor loadings <0,7
2.	Indicator Reliability	According to Hair et al. (2017), the reliability indicator is a square that is in the external load of the standard indicator, which can represent how many types there are in an indicator. Reliability indicators can also be called Outer loadings.	Valid if the Indicator reliability valued over >0,5	Invalid if the Indicator reliability valued not over than <0,5
3.	Average Variance Extracted	Menurut Hair et al. (2022), average variance extracted adalah ukuran yang digunakan dalam menentukan validitas konvergen di tingkat konstruk.	Valid if the value of average variance extracted >0,5	Invalid if the value of average variance extracted <0,5

3.7.2.2 Reliability Test

To ensure the consistency of the measurement scale used in this research, a reliability test was conducted following the approach outlined by Hair et al. (2019). This test calculates two key metrics: Composite Reliability and Cronbach's Alpha. The details of these metrics and their corresponding criteria will be presented in a table for further reference.

Table 3.3 Reliability Test

No.	Size Validity	Definition	Required Value	
1.	Composite Reliability	According to Hair et al. (2019), composite reliability is a measurement based on the assumption that each item needs to be given a similar value in terms of individual item reliability, resulting in dissimilar values for each item.	Valid, if it has a composite reliability value > 0.7	invalid, if it has a composite reliability value > 0.7
2.	Cronbach's Alpha	According to Hair et al. (2019),	Valid if it has a Cronbach's	invalid if it has a Cronbach's

		Cronbach's Alpha is a measure of reliability with internal consistency with assumptions or assumptions if the indicators used are the same.	Alpha value > 0.7	Alpha value > 0.7

3.7.3 Reseach Data Analysis with SEM

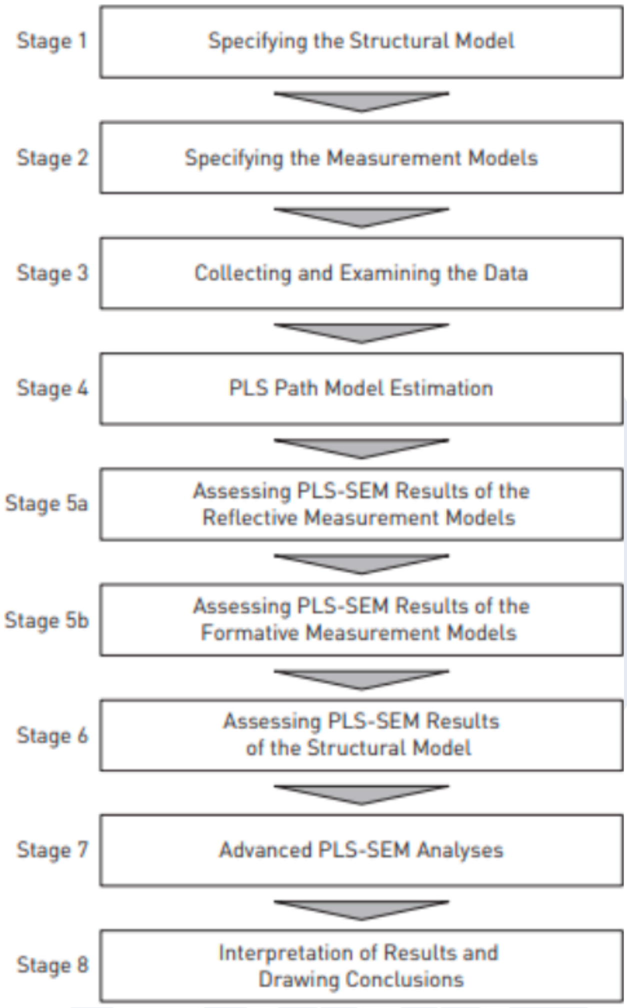
According to Malhotra et al. (2017), structural equation modeling or SEM is a method used to view the relationship between variables, as well as evaluate the quality of each variable when combined with a research model. SEM has two types, namely:

1. Covariance Based Structural Equation Modeling (CB-SEM)

Covariance Based Structural Equation Modeling is a method with a type estimation approach or general factor model, which can accommodate formative measurement models. Covariance based SEM can measure estimates of all model parameters (Bollen & Davies; Diamantopoulos et al., in Hair et al., 2022).

2. Partial Least Squares Structural Equation Modeling (PLS-SEM)

Partial Least Squares Structural Equation Modeling is a model used in developing theory in exploratory research, so that it can focus more on the objects used. Partial Least Squares SEM involves combining indicators based on linear methods to form composite or combined variables (Hair et al., 2022).



Picture 3.5 PLS-Structural Equation Modeling

Source: Hair et al., (2022)

Breaking down the stages of SEM according to Hair et al. (2022):

The Stages of Structural Equation Modeling (SEM): SEM involves a series of steps to analyze relationships between variables. Here's a breakdown of the key stages:

a. Specifying the Structural Model (Stage 1):

This initial stage combines your research question with the SEM framework. It visually depicts the hypothesized relationships and correlations between the variables you're studying.

b. Specifying the Measurement Models (Stage 2):

This stage focuses on the link between the underlying concepts (latent variables) in your model. It also ensures that the indicator variables (the questions or measures used in your survey) adequately represent their corresponding latent variables. Measurement theory guides this assessment, ensuring the data collected is suitable for partial least squares SEM analysis. In other words, if you're testing hypotheses about relationships between variables, you need to demonstrate that your measurement tools accurately capture these variables.

c. Collecting and Examining Data (Stage 3):

This crucial stage involves data collection and analysis. While both qualitative and quantitative data can be used in SEM, partial least squares, SEM typically relies on primary data collected through surveys or questionnaires. Once the data is collected, it must be processed using appropriate software. In this research, SmartPLS 4 was used for data processing.

d. Path Model Estimation (Stage 4):

This stage delves into the specific methods used in partial least squares (PLS) SEM. It emphasizes that the data used for measurement comes from respondent answers to survey questions. PLS SEM then estimates the unknown elements within the model based on the collected data.

e. Assessing PLS-SEM Results (Stage 5):

This final stage focuses on evaluating the results of the measurement and structural models. The measurement model assesses the correlation between each indicator variable and its corresponding latent variable.

This helps determine whether the theoretical model aligns with the collected data. The goal of PLS-SEM is to maximize the explained variance in the path model (the relationships between variables). Evaluating the quality of the measurement and structural models, along with the statistical significance of the path coefficients, is crucial in PLS-SEM analysis.

Path coefficients, representing the strength and direction of relationships between variables, are the most important element in the structural model, with t-values providing complementary information.

Essentially, assessing PLS-SEM results involves examining both the measurement and structural models.

i. Reflective Measurement Models

   This reflective measurement model consists of composite reliability in evaluating factor loading, reliability indicators, and average variance extracted in evaluating convergent validity. This model also includes discriminant validity.

ii. Formative Measurement Models

   At this stage, the indicators that you want to measure will be determined by the author. Each indicator that will be measured needs to be identified. In the formative measurement model there are 3 stages, namely assessing convergent validity, assessing whether there is a correlation or not with the formative measurement model, and assessing the significance level of each variable.

f. Assessing PLS-SEM Results of the Structural Model (Stage 6):

At this stage, it consists of six steps in testing the results of the structural model, namely:

i. Structural equation models (SEM) can be valuable tools for dealing with collinearity, where multiple variables are highly correlated. While some might downplay collinearity's impact, it can lead to inaccurate estimates in traditional regression models. SEM can help address collinearity by explicitly modelling the relationships between these correlated variables.

ii. In assessing the effectiveness of a structural model built with reflective measures, researchers delve into the significance of the relationships between variables. This evaluation hinges on two key elements: p-values and path coefficients. P-values indicate how likely it is that the observed relationships between variables could be due to chance, while path coefficients quantify the strength and direction of these influences. By analyzing both, researchers can determine if the model aligns with their hypotheses and effectively addresses the research question, making this assessment a crucial bridge between theory and the study's core problem formulation.

iii. Assess the level of R^2

Hair et al. (2014) argue R^2 represents the total amount of variance explained in each variable used in the research model framework. A minimum value of R^2 0.25 is considered weak, a value of 0.5 is considered moderate, and 0.75 is considered strong.

iv. Assess impact f^2

F^2 impact assessment allows one to see the help of exogenous construction on the variables in the R^2 value. A minimum value of $f^2 = 0.02$ is considered weak, a value of 0.15 is considered moderate, and 0.25 is considered strong.

v. Assessing predictive relevant relationships of Q^2

In the structural model, if the value of $Q^2 > 0$, then the model has relevance to the related dependent variable. The resulting values of ^{Q2} are obtained by blindfolding.

vi. Assess impact Q^2

The results of the Q^2 values obtained by blindfolding show whether the path model can predict the values of the variables being tested well or not.

g. Advance PLS-Sem Analyses (Stage 7):

In the seventh stage, the author needs to carry out an analysis of all the data that has been collected, as well as testing with the application media used.

h. Interpretation of Results & Drawing Conclusions (Stage 8):

In the final stage, the author explains the results of the research. And the author will draw conclusions from the research that the author has conducted.

3.7.4 Hypotheses Test

Hair et al. (2019) state that to evaluate the predetermined hypotheses and determine whether they are accepted or rejected, it is not sufficient to simply rely on the type of hypothesis that meets the criteria. Instead, several guidelines must be followed when testing hypotheses, including:

1. Path Coefficient

Path Coefficient is an appropriate structural model correlation of standard beta in regression analysis to measure whether there is empirical support for the hypothesis that has been determined.

2. P-value

The P-value has a measurement function so that you can find out whether the hypothesis is accepted or rejected. A P-value < 0.05 means that the two variables contained in the hypothesis have a significant impact or influence. Meanwhile, a P-value with a value > 0.05 means that the two variables in the hypothesis do not have a significant impact or influence.

3. T - Value

T - Value is a limit for determining the significance of a coefficient. Empirical T - Value must be greater than the critical T - Value. Critical T - Value has criteria: a value > 1.65 for a one-sided test and a value > 1.96 for a two-sided test (Hair et al., 2022).