CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter explains the research methodology that was used to achieve the study's objective. These include research design, population and sample size, sampling method, research instrument/questionnaire development, data collection and measurement methods, hypothesis testing, and data and instrument validity and reliability. According to Creswell, (2007), a methodology is a group of complementary methods that can provide data and findings that address the research question and align with the researcher's objectives. The methodology is illustrated in the following flowchart.

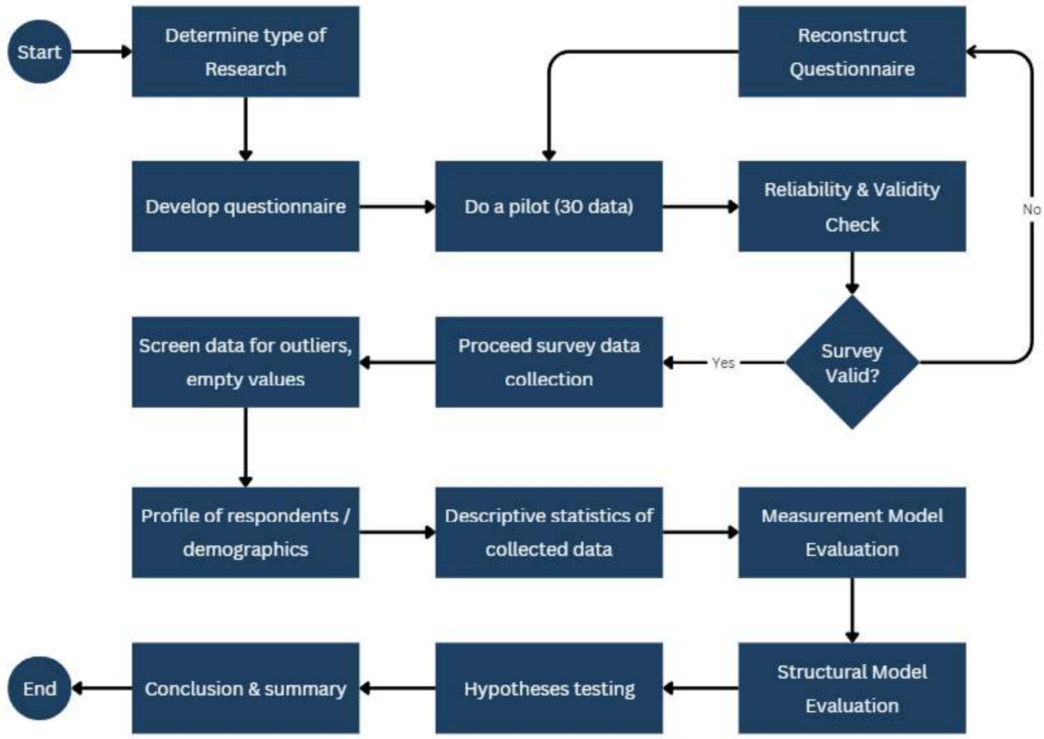

Figure 3.1 Methodology Flowchart

3.2 Type of Research

The framework used in this paper is the research onion developed by Saunders & Thornhill (2015). The research onion is a framework that can be adapted to almost any research technique and used in various contexts. Each layer of the model represents a stage of the research process, which helps in the development of a research methodology.

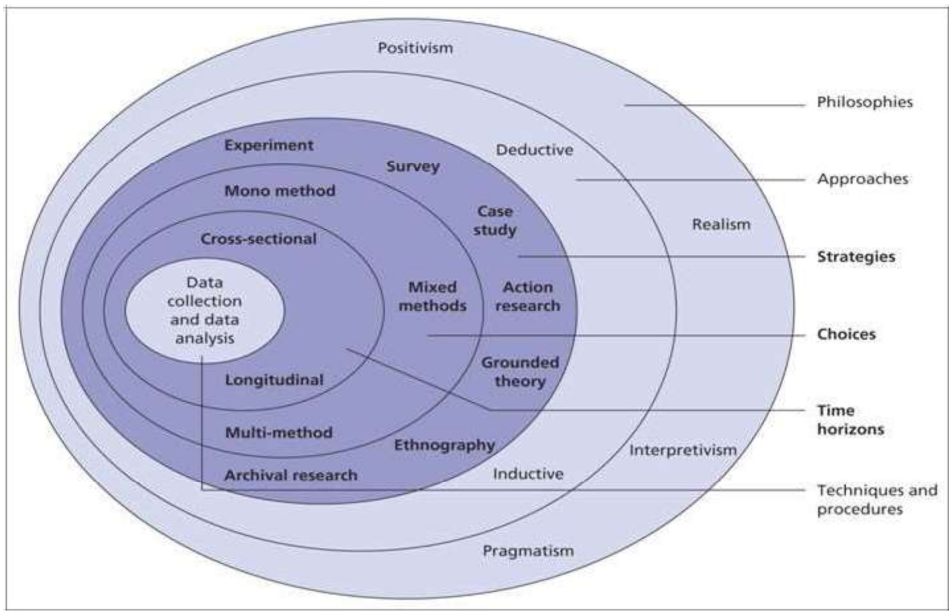

Figure 3.2 Research Onion Diagram

Source: Saunders, et al., 2015

The research methods tree can be expanded into the research onion. The research onion's layers can be described from the outside in as follows *(Lewis & Thornhill, 2019; Saunders & Thornhill, 2016)*:

Positivism was selected as the first layer of philosophy because the method is typically deductive, highly structured, uses samples and measurements, and typically employs quantitative methods of analysis. This study chose positivism because it allows for the formulation of testable research questions and hypotheses.

The **deductive** approach is the second layer employed. Because this research is measuring the relationship between variables, therefore quantitative methods are more appropriate it can provide statistical evidence to support or reject the hypothesis.

This study utilized a **survey** research design, which involves selecting a representative sample from the population to identify contributing factors and gather substantial data to address the research question.

The fifth layer adopted a **cross-sectional** approach to analyze the variables within the research framework. Data collection focused on a single time period in February 2025. The study involved a sample of respondents specifically targeting the general public having experience in using Self Service Technology (SST) in the Greater Jakarta Area.

3.3 Source of Data

To reach a scientific conclusion, data collection and analysis must be conducted within the research study. This study uses quantitative data derived from various quantitative variables whose values are determined by scoring survey / questionnaire responses.

The data used in this research was sourced from:

1) *Primary data source*

   The primary data for this research was collected through a questionnaire survey. This study generated this survey specifically to address and answer the research topic.

2) *Secondary source of data*

   Secondary data for this research was collected from existing data derived from various sources, such as books, scholarly journals, and prior studies, that predate the current research and can serve as valuable theoretical references.

This survey was distributed using Google Forms to allow for easy access and ensure sufficient data for results, conclusions, and hypotheses. To get more responses, it was distributed through WhatsApp and other online channels.

3.4 Population and Sample

When conducting studies or research, it is often impractical or impossible to gather data from the entire population. Therefore, a sample, a subset of the population, is selected to represent the larger group. By analyzing the sample, researchers can draw conclusions about the entire population.

The method utilized in this investigation was non-probability convenience sampling. The criteria for selecting this sample are:

1. Individual age 18 or higher
2. Have a general understanding about SST in restaurant, such as kiosk, mobile phone ordering, or stand tablet
3. Have experience ordering in restaurant using SST such as kiosk, mobile phone ordering, or stand tablet
4. Resides in the greater Jakarta area (Jakarta, Bogor, Depok, Tangerang, or Bekasi), which generally where various SST has been deployed in some restaurants for past several years.

3.4.1 Sample Size

The statistical method used in this research is PLS-SEM. According to Hair et al. (2014), the sample size significantly influences the appropriateness and statistical power of multiple regression. Therefore, determining the sample size is crucial, as it impacts the generalizability of the findings.

Table 3.1 Cohen Table

Source: A primer on partial least squares structural equation modeling (PLS-SEM) by Hair, et. al (2014)

Exhibit 1.7 Sample Size Recommendation a in PLS-SEM for a Statistical Power of 80%

Maximum Number of Arrows Pointing at a Construct	*Significance Level*											
	1%				*5%*				*10%*			
	Minimum R^2				*Minimum* R^2				*Minimum* R^2			
	0.10	*0.25*	*0.50*	*0.75*	*0.10*	*0.25*	*0.50*	*0.75*	*0.10*	*0.25*	*0.50*	*0.75*
2	158	75	47	38	110	52	33	26	88	41	26	21
3	176	84	53	42	124	59	38	30	100	48	30	25
4	191	91	58	46	137	65	42	33	111	53	34	27
5	205	98	62	50	147	70	45	36	120	58	37	30
6	217	103	66	53	157	75	48	39	128	62	40	32
7	228	109	69	56	166	80	51	41	136	66	42	35
8	238	114	73	59	174	84	54	44	143	69	45	37
9	247	119	76	62	181	88	57	46	150	73	47	39
10	256	123	79	64	189	91	59	48	156	76	49	41

Source: Cohen, J. A power primer. *Psychological Bulletin*, 112, 155–519.

According to Hair et al. (2014), the minimum coefficient of determination (R^2) is influenced by the significance level, the number of relationships between constructs, and the sample size, as illustrated in the table above. Cohen (1988) suggests that an R^2 value of 0.25 represents moderate explanatory power, which is the most commonly assumed threshold. Based on this, the present study adopted an R^2 value of 0.25 and a significance level (α) of 0.05 (5%).

The latent variable "Intention to use SST" is influenced by three predictors: Performance Expectancy, Effort Expectancy, and Social Influence, each represented by an arrow pointing toward it. Similarly, the latent variable "Actual Use of SST" is influenced by two predictors: Intention to use SST and Facilitating Conditions. Therefore, the maximum number of predictors in this study is 3.

With $R^2 = 0.25$, $\alpha = 0.05$, and maximum number of predictors = 3, then based on Cohen's table, the minimum sample this research need to collect is 59 samples.

The second method used to calculate the sample size is GPower analysis *(Erdfelder et al., 1996)*, which is a widely recognized approach for determining sample size in social and behavioral research. Considering the effect size (f^2) value of at least 0.15 (medium effect size) with α = 0.05 and a statistical power of 0.8, the required sample size calculated by G Power is 77 (Figure 3.3).

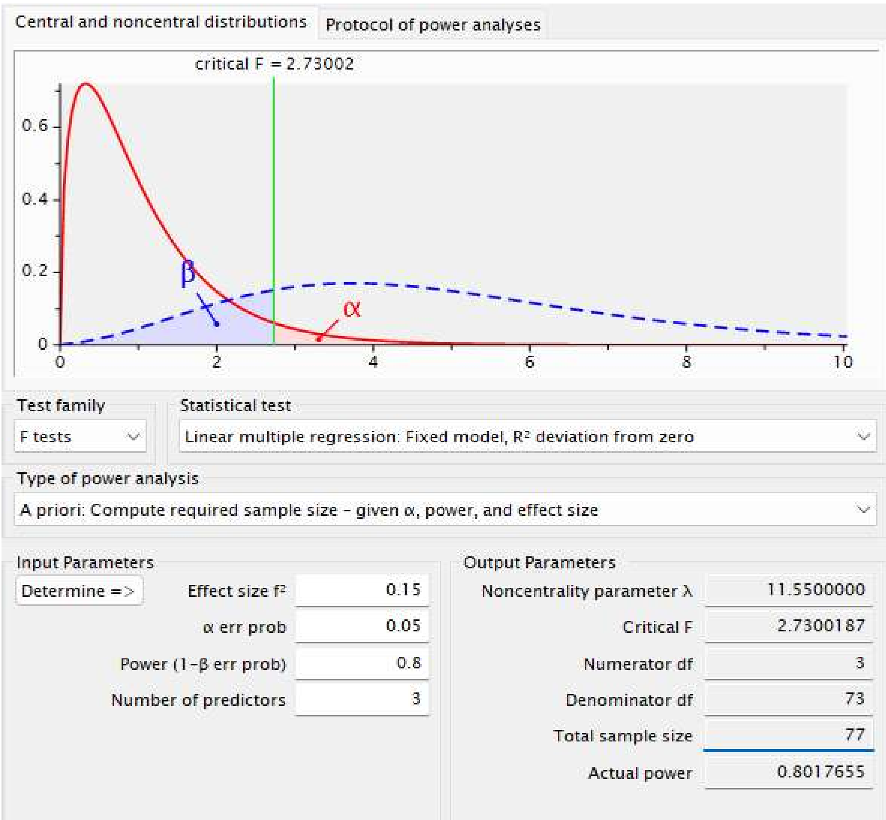

Figure 3.3 G Power Analysis

Source: Data processed by GPower software v3.1.9.7 (2024)

Based on the guidance from the two sources mentioned above, the researcher decided to use 100 samples for this study. This sample size exceeds the minimum threshold and aims to enhance both accuracy and generalizability.

3.5 Data Collection

Data collection was conducted through an online questionnaire. The questionnaire was distributed via Google Forms, shared through messaging platforms such as WhatsApp. This study utilized a five-point Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral (Neither Agree nor Disagree), 4 = Agree, and 5 = Strongly Agree.

3.6 Measurement of Variables

Based on research framework in Figure 2.2, this study employed three independent variables (predictors): Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI). These constructs directly influence the dependent variable (outcome), Intention to Use SST (BI), which subsequently drives the Actual Use of SST (UB). Additionally, the model incorporates Facilitating Conditions (FC) and Interpersonal Service Quality (SQ) as moderating variables.

Table 3.2 Operational Variables

Variable	Construct	Code	Measurement Item	Source
Performance Expectancy (PE)	Perceived Usefulness (PU)	PE1	Using self-service technology in restaurants allows me to place orders more efficiently.	Davis 1989; Davis et al. 1989
		PE2	Self-service technology enhances my ability to customize my order.	
	Outcome Expectations (OE)	PE3	Using self-service technology will reduce the time I spend ordering food.	Compeau and Higgins 1995b; Compeau et al. 1999
		PE4	Other diners may perceive me as tech-savvy when I use self-service technology.	
Effort Expectancy (EE)	Perceived Ease of Use (PEU)	EE1	I find it simple to navigate and interact with self-service technology.	Davis 1989; Davis et al. 1989
		EE2	I can quickly learn how to use self-service technology in restaurants.	

Variable	Construct	Code	Measurement Item	Source
	Ease of Use (EU)	EE3	My interaction with self-service technology in restaurants is clear and understandable.	Moore and Benbasat 1991
		EE4	Overall, I believe that self-service technology in restaurants is easy to use.	
Social Influence (SI)	Subjective Norm (SN)	SI1	My friends and family encourage me to use self-service technology in restaurants.	Ajzen 1991; Davis et al. 1989; Fishbein and Azjen 1975; Mathieson 1991; Taylor and Todd 1995a, 1995b
	Social Factors (SF)	SI2	I use self-service technology because I see others using it in restaurants.	Thompson et al. 1991
	Image (IM)	SI3	People who use self-service technology in restaurants appear more tech-savvy.	Moore and Benbasat 1991
		SI4	Using self-service technology in restaurants is associated with modern dining habits.	
Facilitating Condition (FC)	Perceived Behavioral Control (PBC)	FC1	I have the necessary skills to use self-service technology in restaurants.	Ajzen 1991; Taylor and Todd 1995a, 1995b
		FC2	Restaurants provide adequate guidance for using self-service technology.	
	Facilitating Conditions (FC)	FC3	Assistance is available if I have difficulty using self-service technology.	Thompson et al. 1991

Variable	Construct	Code	Measurement Item	Source
	Compatibility (CM)	FC4	Self-service technology fits well with how I prefer to order in restaurants.	Moore and Benbasat 1991
Interpersonal Service Quality (SQ)	Reliability (RE)	SQ1	Restaurant staff are reliable in assisting with self-service technology issues.	Parasuraman et al. 1985
	Assurance (AS)	SQ2	I feel confident using self-service technology due to staff assistance.	
		SQ3	Restaurants ensure self-service technology is reliable and secure.	
	Empathy (EM)	SQ4	Restaurant staff are approachable when customers need help with self-service technology.	
Behavioral Intention (BI)	Intention to Use (IU)	BI1	I intend to use self-service technology to order in dine in restaurant in the future.	Venkatesh et al. (2003)
		BI2	I plan to use self-service technology to order in dine in restaurant frequently.	
	Willingness to Recommend (WR)	BI3	I would recommend self-service technology in dine in restaurant to others.	
Use Behavior (UB)	Frequency of Use (FU)	UB1	I use self-service technology to order in dine in restaurant frequently.	Venkatesh et al. (2003)
		UB2	I have integrated self-service technology to order in dine in restaurant into my habit.	
	Duration of Use (DU)	UB3	I spend significant time using self-service technology to order in dine in restaurant.	

3.7 Development of Questionnaires

The questionnaire was divided into two sections. The first section collected demographic information including their age, gender, current residency in the Greater Jakarta Area, and general experience using self-service technology in dine-in restaurants. This ensures that the data collected from the survey was relevant to the study.

The second section tests the model described in Figure 2.2. This section includes measurement items based on the operational variable (see Table 3.2), representing each variable and constructs used in the research.

The survey was done anonymously and only responses meeting the predefined criteria was considered valid data for the study. The questionnaire is translated to Indonesian (Bahasa Indonesia) to prevent any potential language misunderstandings.

3.8 Data Analysis Method

3.8.1 Descriptive analysis

Descriptive analysis is the initial step in research involving statistical data, where respondent data is processed to provide an overview of their general information. This analysis helps researchers gain insights into various aspects of respondents, such as their characteristics and perceptions of the research variables, using measures like frequency percentages, standard deviation, and mean.

As a statistical technique, descriptive analysis summarizes, organizes, and highlights the main features of a dataset. It helps to understand data distribution, central tendencies, and variability, uncovering patterns and insights in this research.

3.8.2 Partial Least Square (PLS) - Structural Equation Model (SEM)

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary method for data analysis. PLS-SEM is a variance-based structural equation modeling technique that is widely used in social sciences and business research to estimate complex models involving latent variables. It is suitable for exploratory research and situations where the theoretical foundation is still developing.

PLS-SEM is chosen for this study due to the following reasons:

1) PLS-SEM is effective in exploratory research contexts where the goal is to identify key relationships rather than confirm well-established theories.

2) PLS-SEM can analyze models with many constructs, indicators, and relationships without imposing strict distributional assumptions.

3) PLS-SEM is robust in analyzing data even when sample sizes are relatively small.

4) The technique focuses on maximizing explained variance in the dependent variables, making it suitable for predictive modeling.

3.8.3 Data Preparation

To ensure the validity of the questionnaire's contents, the data was cleaned to eliminate missing values and outliers that could impact the results. Following this, reliability and validity tests were conducted to assess the instrument's accuracy and ensure it produced consistent and reliable data for the research.

3.8.4 Evaluation of Measurement Model (Outer Model)

According to Hair et al. (2014), when applying PLS-SEM, researchers need to follow a multi-stage process that includes specifying the inner and outer models, collecting and examining data, conducting model estimation, and evaluating the results.

The first step in PLS-SEM analysis is evaluating the outer model (or measurement model). This step aims to determine how well the items (questions) load onto their hypothesized constructs. Analyzing the outer model involves examining the unidirectional predictive relationships between each latent construct and its associated observed indicators. This ensures that the indicators adequately represent the constructs being measured *(Hair, Ringle, & Sarstedt, 2011)*.

Generally, there are two distinct measures of the indicators in PLS-SEM that are reflective and formative outer model *(Becker, Klein, & Wetzels, 2012)*. The assessment of reflective outer model involves the examining of reliabilities of the individual items (indicator reliability, outer loading), internal consistency (Cronbach alpha and composite reliability), convergent validity (average variance extracted or AVE) and discriminant validity (Fornell-Larcker criterion, cross loading, HTMT criterion) *(Hair et al., 2014)*.

a. Indicator Reliability

   Outer loadings indicate how effectively each survey item measures its intended construct. A high loading (above 0.70) suggests a strong correlation between the item and the construct. For exploratory research, values between 0.60 and 0.70 are considered acceptable.

b. Internal Consistency Reliability

   To determine the reliability of a construct, the most commonly used method is measuring its internal consistency through Cronbach's Alpha and Composite Reliability (CR / ρC), as suggested by Hair et al. (2011). A CR value greater than 0.7 indicates acceptable reliability, showing that the construct items are consistent.

c. Convergent Validity

   Next, we assess convergent validity using the Average Variance Extracted (AVE). An AVE value greater than 0.5 indicates acceptable convergent validity, demonstrating that the construct accounts for more than half of the variance in its associated indicators. This confirms that the indicators effectively represent the construct.

d. Discriminant Validity

Finally, to assess discriminant validity, we can apply the Fornell-Larcker Criterion, which requires the square root of the AVE for each construct to be greater than its correlation with any other construct *(Fornell & Larcker, 1981)*. This indicates sufficient discriminant validity. Additionally, the Heterotrait-Monotrait (HTMT) Ratio can be used as an alternative. A HTMT value below 0.85 (or 0.90 in certain contexts) confirms that the constructs are conceptually distinct from one another *(Ab Hamid, Sami, & Mohmad Sidek, 2017)*.

3.8.5 Evaluation of Structural Model (Inner Model)

The structural model (referred to as the inner model) in PLS-SEM represents the relationships between the latent variables themselves, representing the theoretical framework of the study. It tests the hypotheses about how latent variables influence each other.

The fundamental criteria for evaluating a structural model in PLS-SEM, as outlined by Hair et al. (2014), are:

a. Collinearity

A related measure of collinearity is the Variance Inflation Factor (VIF). To assess collinearity, the VIF values of all predictor constructs in the structural model should be examined. VIF values below the threshold of 5 indicate that collinearity among the predictor constructs is not a significant issue in the structural model.

b. Coefficient of Determination (R^2)

The coefficient of determination measures the explained variance of endogenous latent variables. It indicates the amount of variance in the dependent variable explained by its predictors. Values range from 0 to 1, with higher values indicating better explanatory power (e.g., 0.25 = weak, 0.50 = moderate, 0.75 = strong).

c. Effect Size (f^2)

Effect size evaluates the contribution of each predictor variable to the R^2 value of the dependent variable by assessing how removing an independent variable impacts the R^2. The values are categorized as small (0.02), medium (0.15), or large (0.35).

d. Path Coefficients

The path coefficients represent the strength and direction of the relationships between latent variables in the structural model. Estimated values range from -1 to +1, where values closer to ±1 indicate stronger relationships. The significance of these relationships is tested using the bootstrapping procedure, which provides p-values and t-statistics to determine whether the relationships are statistically significant.

e. Predictive Relevance (Q^2)

The model's out-of-sample predictive power is evaluated using the blindfolding procedure. A Q^2 value greater than 0 indicates that the model has predictive relevance, meaning it can accurately predict the observed data for endogenous constructs.

3.9 Hypothesis Testing

The t-test is a statistical method used to determine whether a variable has a significant effect on the study. To conduct this test, this study used bootstrapping to generate data for analysis. According to Hair et al. (2018), bootstrapping is employed to evaluate the relationship between the variables under study. For the hypothesis to be considered plausible, it must have a significance level of 5% (p-value ≤ 0.05).

If the t-statistic is lower than the critical value from the t-table, the relationship is deemed insignificant. For a one-tailed hypothesis at the same confidence level, the t-table value is 1.645. For a two-tailed hypothesis in that confidence level, the t-table value is 1.96. These thresholds are essential for interpreting whether the results indicate a significant association between the variables *(Hair et al., 2018)*.