CHAPTER III
RESEARCH METHODOLOGY

3.1 Research Paradigm

Thomas Kuhn (1962) contends that a paradigm encompasses a collection of beliefs, values, techniques, and methods employed by a specific scientific community in their research endeavors. Egon Guba and Yvonna Lincoln (1988) propose that the research paradigm represents the researchers' comprehension of specific problems along with criteria used to assess problem-solving approaches.

The author's research is a quantitative study focusing on specific populations and samples, employing measurable variables and statistical testing. The chosen research paradigm is positivism, emphasizing an objective and empirical approach to gather insights and draw conclusions. The positivism methodology places a significant emphasis on experimentation. It involves formulating hypotheses in propositional or interrogative formats concerning the causal relationship between phenomena. Subsequently, empirical evidence is collected, and the amassed data is thoroughly analyzed to formulate a theory. This theory serves to elucidate the impact of the independent variable on the dependent variable (Rehman & Alharthi, 2016).

Scholars classify primary research methodologies into two distinct approaches: exploratory and conclusive designs (Malhotra, 2010). Exploratory studies facilitate problem identification and knowledge development, whereas conclusive research focuses on hypothesis verification and relationship analysis. Within conclusive research, scholars recognize two subcategories: descriptive investigations that profile attributes of subjects or phenomena (Zikmund, 2013), and experimental studies that establish causal linkages between variables (Malhotra, 2010).

3.2 Research Object and Subject

3.2.1 Object of Research

The research object of this study is the causal network linking influencer characteristics to customer attitudes, brand equity (awareness and association), and ultimately online purchase intention in Indonesia's live streaming commerce ecosystem. Influencer credibility, attractiveness, and marketing content serve as independent variables expected to influence consumer attitudes and brand equity dimensions, which in turn mediate their effect on purchase intention.

3.2.2 Research Subject

The research subjects in this study are Indonesian consumers, who serve as the primary source of observational and behavioral data. These individuals were specifically chosen for their active engagement live commerce. To ensure the relevance and richness of the data, the study focuses on consumers who have demonstrated verified and sustained participation in live streaming shopping environments.

To qualify as a participant, individuals had to meet two key engagement criteria. First, they must have attended a minimum of six live streaming sessions within the past six months. This threshold was set to capture consumers who are not just casual viewers but have developed a consistent habit of engaging with live stream content, allowing for more informed observations about their preferences, motivations, and shopping behaviors.

Second, participants must have made at least one electronics-related purchase through popular live commerce platforms in Indonesia, specifically TikTok Shop or Shopee Live. By narrowing the scope to electronics purchase.

3.3 Population and Sampel

3.3.1 Population

In research methodology, the term population refers to the complete set of elements possessing defined attributes that researchers identify for investigation and analysis to derive meaningful findings (Sugiyono, 2016). Population refers to the entirety of research subjects (Arikunto, 2002). Population encompasses all variables related to the researched issue (Nursalam, 2003). Therefore, the target population of this study is someone who uses social media who has purchased product online.

3.3.2 Sampel

As per Sugiyono (2021), a sample is a portion of the population that is selected and measured statistically to study a particular object. It is also a small part representing a larger population. A good sample should share characteristics similar to the entire population (Zikmund, 2013). Based on the concepts above, the sampling criteria for this study are a user who has purchased electronics & gadget via live streaming who lives in Jabodetabek.

Hair et al. (2022) provide guidelines for determining appropriate sample sizes in research studies, emphasizing the importance of adequate statistical power and model complexity. Their updated recommendations suggest that studies should include a minimum of 100-150 respondents to ensure reliable results, with each latent variable being measured by at least 3-5 indicators. These standards account for modern analytical requirements in structural equation modeling.

3.4 Variable Operation

In this study, there is 3 independent variable, 3 mediating variables, and 1 dependent variable, which is a latent variable. Therefore, it requires the assistance of measured variables, also known as indicators. The measurement scale for indicators in this research employs a Likert scale ranging from 1 for "Strongly Disagree (SD)" to 4 for "Strongly Agree (SA)".

The 4-point forced-choice Likert scale was selected to avoid neutral responses and reduce central tendency bias (Chyung et al., 2017). This approach yields more discriminative data in consumer research (Dawes, 2008) and demonstrates superior discriminant validity for measuring purchase intentions (Pavlou & Fygenson, 2006). The format is particularly effective for live commerce studies, where it reduces satisficing behavior by 37% compared to odd-numbered scales (Krosnick & Berent, 1993) while maintaining reliability (Wongkitrungrueng & Assarut, 2020). The research indicators utilized are as follows:

Table 3. 1 Variable Operation

No	Variable	Definition	Indicator	Measurement Scale
1	Influncer Credibility	Influencer credibility encompasses the perceived trustworthiness, expertise, and reliability that followers associate with an influencer within the sphere of influencer marketing. (Martiningsih D, Setyawan A, 2022)	**ICR1**, My favourite influencer is knowledgeable about the products. **ICR2**, My favourite influencer is experienced in using the products. **ICR3**, My favourite influencer seems to be honest. **ICR4**, My favourite influencer is credible and convincing. (Macheka T, et al, 2023 & author modification)	Likert Scale 4

2	Influencer Attractiveness	Influencer attractiveness is the perceived physical appeal, charisma, or aesthetic appeal of an influencer.(Wiedm ann, K.-P, von Mettenheim, W. 2021).	**IAT1**, My favourite influencer is well known. **IAT2**, My favourite influencer is attractive. **IAT3**, My favourite influencer is good-looking. **IAT4**, My favourite influencer is fasionable. (Macheka T, et al, 2023 & author modification)	Likert Scale 4
3	Influencer Marketing Content	Content marketing is a marketing strategy used to attract, engage, and retain an audience by creating and sharing relevant articles, videos, podcasts, and other media. (Mailchimp)	**IMC1**, The content provided detailed product specifications. **IMC2**, The host compared features with competing products effectively. **IMC3**, The host addressed my questions during the stream. **IMC4**, The content felt genuine, not scripted. (Wongkitrungrueng &	Likert Scale 4

			Assarut (2020),Sun et al. (2022), Chen et al. (2021), Audrezet et al. (2020))	
4	Customer Attitude	Customer attitude is how consumers evaluate and act towards a product or brand. (Forbes, 2019)	**ATT1**, My favourite brand meets my expectations. **ATT2**, My favourite brand guarantees satisfaction. **ATT3**, My favourite brand does not disappoint. (Macheka T, et al, 2023 & author modification)	Likert Scale 4
5	Brand Awareness	brand awareness is the degree to which consumers recognize a product by its name. (Keller, 2020)	**BRA1**, My favourite brand comes up first in my mind when making a purchase decision. **BRA2**, I can recognise my favourite brand among competing brands. **BRA3**, I can quickly recall symbols of my favourite brand.	Likert Scale 4

			(Macheka T, et al, 2023 & author modification)	
6	Brand Association	Brand association is anything linked in memory to a brand. (Aaker, 1991)	**BAS1**, This brand is innovative/technically advanced. **BAS2**, This brand cares about customers like me. **BAS3**, This brand is trustworthy and reliable. (Aaker (1991), Delgado- Ballester (2001), Katadata (2025))	Likert Scale 4
7	Purchase Intention	purchase intention is the indication of an individual's readiness to perform a given behavior. (Ajzen, 1991)	**OPI1**, I likely to purchase electronics & gadget products recommended by my favorite influencer. **OPI2**, Products recommended by my favorite influencer affect my buying intention. **OPI3**, My willingness to purchase products recommended by my	Likert Scale 4

			favorite influencer is high. **OPI4**, I would purchase products recommended by my favorite influencer. (Macheka T, et al, 2023 & author modification)	

3.5 Data Collection Techniques

Determining data is an important and strategic step that is determined through primary data obtained in a study. The importance of determining data in research is because there is a goal that must be achieved by the researcher, namely obtaining data that is in accordance with the characteristics of the research and being able to find answers to the phenomenon or problem being researched by the author. Determining the data used in this research to be more objective was carried out through: (Sugiyono, 2019).

This research is using a questionnaire, questionnaire is a data collection technique by distributing questionnaires in which a series of pre-formulated written questions are provided for respondents to answer (Arikunto, 2019). Researchers, using questionnaires, can dig up the information needed through respondents (people who are research subjects). Thus, the questions asked relate to the information (data) needed to solve problems or test research hypotheses. The questionnaire distributed was filled in by consumers who had the intention of purchasing online via live streaming.

This research is using Google Form as a medium for preparing online questionnaires for consumers who have the intention of purchasing online via live streaming. This study employed a 4-point Likert scale for its survey instrument. As

Sekaran and Bougie (2019) explain, the Likert scale measures the intensity of respondents' agreement with presented statements. Additionally, Sugiyono (2019) notes that this scaling method effectively assesses individuals' or groups' attitudes, opinions, and perceptions regarding social phenomena.

Researchers designed a survey with four answer choices. The essence of this scale is to direct respondents to use their opinions and reduce the tendency to focus on the middle value, a 4-point Likert Scale with a value of 1 indicating Strongly Disagree (STS), a value of 2 indicating Disagree (TS), a value of 3 indicating Agree (S) and the highest score of 4 which states Strongly Agree (SS), so that respondents can choose between being pro or con with the statement given. The questionnaire consists of 3 parts, the first part contains a cover letter, the second part contains the respondent profile and respondent selection criteria, and the third part contains statements to measure research indicators.

3.6 Data Analysis Techniques

Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected as the primary analytical method for this study due to its demonstrated advantages in handling complex predictive models with multiple latent constructs (Hair et al., 2022). The research examines a sophisticated network of relationships between influencer characteristics, customer attitudes, brand equity dimensions, and purchase intention - a conceptual framework that benefits from PLS-SEM's ability to simultaneously analyze formative and reflective measurement models while avoiding the stringent data assumptions required by covariance-based approaches (Sarstedt et al., 2022). Particularly relevant to this investigation is PLS-SEM's superior performance with small-to-medium sample sizes (n=150), as it employs a component-based algorithm that maintains statistical power even when the data violates normality assumptions, a common occurrence in Likert-scale consumer behavior research (Kock & Hadaya, 2022).

The predictive orientation of PLS-SEM aligns perfectly with the study's objectives of identifying key drivers of online purchase intention in Indonesia's live streaming commerce context (Dash & Paul, 2021). Unlike covariance-based SEM which focuses on theory confirmation, PLS-SEM emphasizes prediction and explanation of variance in the dependent variables, making it ideal for exploratory research in emerging digital commerce phenomena (Hair et al., 2022). Furthermore, the method's ability to generate latent variable scores enables additional analyses such as importance-performance mapping, which can provide practical insights for marketers seeking to optimize influencer collaboration strategies (Sarstedt et al., 2022). These methodological advantages position PLS-SEM as the most appropriate analytical technique for testing the hypothesized relationships while accounting for the unique characteristics of the research context, including non-normal data distributions and the presence of both formative and reflective constructs in the measurement model.

3.6.1 Measurement Model Analysis (Instrument Test)

In this study, used SmartPLS 4 software. SmartPLS was chosen for its unparalleled balance of usability and rigor, enabling efficient yet robust PLS-SEM execution. Its design aligns with thesis researchers' needs: mitigating computational complexity while ensuring methodological integrity (Hair et al., 2022). As Sarstedt et al. (2023) assert, it remains the "gold standard" for PLS-SEM in exploratory social science research.

The data processing was carried out twice, pre-test and main-test. The pre-test process was conducted to test whether the proposed indicators and variables were appropriate and representative of the desired objectives by collecting a sample of at least 30 (Sugiyono, 2017). The main test was conducted after confirming that the indicators and variables were suitable for testing on a large number of respondents in accordance with the research criteria. In this process, the processing was conducted comprehensively and was more complex than the pre-test processing. At this stage, the proposed hypotheses were processed to determine the final results.

The pre-test is needed to determine the general validity and reliability to assess how well the elements represent each instrument and the consistency of each variable in representing the research instrument, while the main-test data processing is conducted more comprehensively and complexly than the pre-test data processing.

3.6.1.1 Validity Test

The validation of research instruments constitutes a critical phase in structural equation modeling (SEM) to ensure both the validity and reliability of measurement tools (Hair et al., 2022). Within the PLS-SEM framework, this process is formally termed outer model evaluation, serving to verify that observed indicators accurately reflect their corresponding latent constructs (Sarstedt et al., 2023). Establishing instrument reliability represents a fundamental prerequisite for subsequent validity testing, as unreliable measures cannot yield valid results (Kline, 2023).

a.) Convergent validity

Convergent validity is a critical step in measurement model testing, examining the degree to which indicators correlate with their respective latent constructs (Hair et al., 2022). This assessment employs two primary metrics: factor loadings and average variance extracted (AVE) values. Following contemporary psychometric standards, indicator loadings should ideally exceed 0.70 to demonstrate strong reliability, though values above 0.50 may be retained in exploratory research contexts (Sarstedt et al., 2023). These thresholds align with the principle that higher factor loadings indicate greater shared variance between the indicator and its construct (Kline, 2023).

b.) Discriminant Validity

Discriminant validity ensures constructs are empirically distinct (Hair et al., 2023). The Fornell-Larcker criterion requires the square root of each construct's AVE to exceed its correlations with other constructs

(Sarstedt et al., 2022), while cross-loading analysis verifies indicators load more strongly on their assigned construct (>0.70) than others (Kline, 2023).

The heterotrait-monotrait (HTMT) ratio provides additional rigor by comparing within-construct to between-construct correlations, with values below 0.85-0.90 indicating discriminant validity (Henseler et al., 2024). This method detects validity issues 15-20% more effectively than traditional approaches (Dash & Paul, 2023).

Together, these complementary tests - Fornell-Larcker, cross-loadings, and HTMT - form a robust validation framework (Franke & Sarstedt, 2023). Their combined use is particularly valuable in consumer research where constructs often overlap conceptually (Chen & Wang, 2024), ensuring measurement models meet rigorous psychometric standards.

From the explanation above, the following is a table of measurements and acceptance criteria.

Table 3. 2 Table of Measurements and Acceptance Criteria (Validity Test)

No	Type of Validity	Measurement Index	Acceptance Criteria
1	Convergent validity	Outer loadings	Loadings > 0.70
		Average Variance Extracted (AVE)	AVE ≥ 0.50
2	Discriminant validity	Cross-loadings	indicator loads highest on its construct (Hair et al., 2022; Amora, 2021)
		Fornell–Larcker criterion	The construct has a higher indicator value compared to other constructs (Hair, et al., 2022)
		Heterotrait–Monotrait ratio (HTMT)	A construct is said to be weak if the value is more than 0.85 (Henseler et al., 2015)

3.6.1.2 Reliability Test

Reliability testing is a test of the level of consistency and reliability of research instruments, meaning that the instruments can provide the same results when tested repeatedly. In SEM analysis, reliability testing can be viewed in two ways, namely Cronbach's Alpha and Composite Reliability. However, Ghozali & Latan (2015) suggest that in reliability testing, construct reliability should be assessed using composite reliability because Cronbach's Alpha often yields lower values. Therefore, in this study, construct reliability is assessed using composite reliability. If the composite reliability value for each construct variable is > 0.7, the research variable is considered to have high reliability and meets the reliability testing criteria (Ghozali & Latan, 2015). Below are the table of measurements and acceptance criteria. Below are the measurements and acceptance criteria.

Table 3. 3 Table of Measurements and Acceptance Criteria (Reliability Test)

No	Statistical Measure	Threshold / Criterion
1	Cronbach's alpha	≥ 0.70; ≥ 0.60 acceptable in exploratory studies (Hair et al., 2022; Sarstedt et al., 2021; Hair et al., 2022)
2	Dijkstra–Henseler's ρ_a (Rho_a)	≥ 0.70; lies between α and ρ_c as the most accurate reliability estimate (Sarstedt et al., 2021; Dijkstra & Henseler, 2015)
3	Composite reliability (Rho_c)	≥ 0.70; assesses internal consistency without assuming tau-equivalence (Hair et al., 2022; SmartPLS thresholds, 2024)

3.6.2 Descriptive Analysis

Descriptive statistics serve as a fundamental analytical approach for summarizing and presenting key characteristics of research data (Allen et al., 2021). This method enables researchers to systematically organize, simplify, and communicate complex datasets through measures of central tendency (mean, median, mode) and dispersion (standard deviation, range) (Field, 2023). As emphasized by contemporary methodology texts, descriptive analysis provides the essential foundation for understanding sample distributions before proceeding to inferential statistics (Pallant, 2022).

In behavioral and social science research, descriptive statistics typically include both numerical summaries and visual representations such as frequency tables, histograms, and box plots (Tabachnick & Fidell, 2021). Recent methodological guidelines highlight the importance of reporting complete descriptive statistics, including measures of skewness and kurtosis when assessing normality assumptions (Byrne, 2023). For survey-based studies, demographic characteristics (age, gender, geographic location) form a crucial component of descriptive reporting to establish sample representativeness (Wilson et al., 2022)..

3.6.2.1 Respondent Profile

The demographic percentage analysis of respondents from the collected data can be calculated using the following formula:

$$P = \frac{\sum fi}{n} x\ 100 \qquad (3.1)$$

P = percentage of respondents

$\sum$fi = number of respondents with a specific answer

n = total number of respondents

3.6.2.2 Respondent Characteristics

This study uses mean analysis to examine the characteristics of the sample, using the following formula:

$$\bar{x} = \frac{\sum fi\, xi}{\sum fi} \qquad (3.2)$$

$\bar{x}$ = average

fi = frequency of i

xi = data of i

3.6.3 Structural Model Analysis (Hypothesis Testing)

Hypothesis testing represents a systematic approach for evaluating theoretical propositions through empirical data analysis (Hair et al., 2023). Within the structural equation modeling (SEM) framework, this process involves examining the structural (inner) model, which depicts the hypothesized causal relationships between latent constructs (Sarstedt et al., 2022). The analysis employs advanced resampling techniques, specifically bootstrapping (typically 5,000 subsamples) and blindfolding procedures, to generate robust estimates of path coefficients and their statistical significance (Henseler et al., 2024).

3.6.3.1 Model fit evaluation

Model fit testing is a test conducted to describe the suitability or appropriateness of the model developed in the study. In this study, several tests were conducted.

a.) Testing the Coefficient of Determination (R^2)

serves as a crucial metric for evaluating the explanatory power of structural models in partial least squares structural equation modeling (PLS-SEM) (Hair et al., 2022). This test quantifies the proportion of variance in endogenous (dependent) latent variables that can be accounted for by their corresponding exogenous (independent) latent variables (Sarstedt et al., 2023). In contemporary SEM literature, endogenous variables are operationally defined as those influenced by other constructs in the model, while exogenous variables represent the influencing factors (Kline, 2023).

Modern guidelines for interpreting R^2 values in behavioral research suggest the following thresholds (Henseler et al., 2024):

- $0.25 \leq R^2 < 0.50$ suggests weak predictive power
- $0.50 \leq R^2 < 0.75$ indicates moderate predictive power
- $R^2 \geq 0.75$ demonstrates strong predictive power

Recent methodological studies emphasize that these benchmarks should be contextualized within specific research domains (Dash & Paul, 2023). For instance, in consumer behavior research examining complex phenomena like purchase intention, R^2 values between 0.30-0.60 are typically considered acceptable (Li et al., 2023). Furthermore, advanced applications now recommend complementing R^2 with the predictive relevance metric (Q^2) to provide a more comprehensive assessment of a model's explanatory and predictive capabilities (Shmueli et al., 2023).

b.) Testing the Goodness of Fit (GoF)

The Goodness-of-Fit (GoF) test serves as a comprehensive evaluation of a structural equation model's overall validity by simultaneously assessing both measurement and structural components (Hair et al., 2023). This global fit index, calculated as the geometric mean of average communality and average R^2 values, provides a singular metric ranging from 0 to 1, where higher values indicate superior model fit (Sarstedt et al., 2022). Contemporary research emphasizes that GoF is particularly valuable in PLS-SEM for comparing competing models and evaluating overall predictive performance (Henseler, 2020).

The computation of GoF follows the formula:

$$GoF = \sqrt{(average\ communality\ x\ average\ R^2)} \qquad (3.2)$$

Where communality values should meet the minimum threshold of 0.50 as established in seminal psychometric literature (Fornell & Larcker, 1981). Modern guidelines categorize GoF results as follows (Wilson et al., 2023):

- $0.10 \leq GoF < 0.25$ suggests small/weak model fit
- $0.25 \leq GoF < 0.36$ indicates moderate/acceptable fit
- $GoF \geq 0.36$ demonstrates large/strong fit

Recent methodological studies have identified several critical considerations for GoF interpretation (Li et al., 2022):

The index should complement rather than replace other fit measures (SRMR, NFI)

3.6.3.2 Significance Test of Influence

This study employs rigorous statistical testing to examine the hypothesized relationships between constructs, utilizing the bootstrapping method - a robust resampling technique that generates empirical sampling distributions (Hair et al., 2022). The analysis evaluates path coefficients through two complementary approaches:

- t-statistic criterion:
  - Significant relationship: t-value > 1.96 ($p < 0.05$)
  - Non-significant relationship: t-value ≤ 1.96 ($p \geq 0.05$)
- p-value interpretation:
  - Statistically significant: $p < 0.05$
  - Not significant: $p \geq 0.05$