CHAPTER III :
RESEARCH METHOD

3.1. Research Paradigm

According to Collis and Hussey (2021), a research paradigm can be defined as "a philosophical framework that guides how scientific research should be conducted" based on people's philosophies and assumptions about the world and the nature of knowledge. It is the overall perspective or framework that guides researchers in understanding social phenomena and their approach to theory or science (Radjab and Jam'an, 2017) and conducting their research (Walliman, 2011). It shapes how researchers view the world, their methods, and the systematic process of seeking truth through research (Samsu, 2017).

Research paradigms play a crucial role in shaping the research process, from determining the research problem to selecting appropriate methodologies and methods for conducting the study (Collis and Hussey, 2021), establish criteria for testing it, and how they interpret social facts (Radjab and Jam'an, 2017). In the context of scientific revolutions, a paradigm encompasses a set of beliefs and dictates that influence what should be studied, how research should be done, and how results should be interpreted (Bell, Bryman, and Harley, 2019).

There are different research paradigms, with the two main ones being quantitative and qualitative. These paradigms have evolved over time and continue to shape the landscape of research with their respective perspectives (Samsu, 2017). The quantitative paradigm focuses on testing theories through measurement and statistical analysis of variables, often involving deductive approaches and hypothesis testing. On the other hand, the qualitative paradigm emphasizes the subjective understanding of phenomena, often through in-depth exploration of experiences and meanings (Radjab and Jam'an, 2017). The history and approaches of qualitative, quantitative, mixed methods, and research and development paradigms demonstrate the long-standing human endeavor to systematically seek truth through scientific inquiry (Samsu, 2017). That is why understanding research paradigms is essential for researchers to establish a coherent and methodologically sound framework for their studies.

This research adopts a positivist paradigm, which is based on the assumption that reality is objective and can be measured through observable phenomena (Bell, Bryman, and Harley, 2019). The positivist approach is suitable for this study as it aims to investigate the causal relationships between various factors influencing the purchase intention of electric vehicles (EVs) in Indonesia. By employing quantitative methods, such as surveys and statistical analysis, allows the research to objectively identify and measure the impact of these factors (Creswell, 2019).

3.2. Research Object and Subject

3.2.1. Object of the Research

The object of this research is to understand the behaviors, perceptions, and purchase intentions of Indonesian consumers toward electric vehicles (EVs). It examines key factors that influence these behaviors, such as perceived benefits, perceived risks, the effectiveness of marketing efforts, and the role of facilitating conditions within the EV market in Indonesia.

3.2.2. Subject of the Research

The subjects of this research are Indonesian vehicle user who have not yet purchased Electric Vehicles (EVs) but possess the financial capacity to do so. These subjects span diverse demographic characteristics including age, gender, income levels, and educational backgrounds, with emphasis on middle and upper-income segments aligned with EV ownership costs. Their existing experience as vehicle owners combined with EV purchase potential makes them valuable informants for understanding adoption factors in Indonesia's automotive market. This subject selection ensures that insights about perceptions, attitudes, and purchase intentions come from individuals who could realistically participate in the EV market, providing practical understanding of the consumer decision-making process.

3.3. Population and Sample

3.3.1. Population

Population refers to the total set of objects or subjects that possess certain characteristics defined by the researcher for study, from which conclusions are drawn.

Population includes not only people but also other objects such as animals, plants, and events that share common traits relevant to the research (Sugiyono, 2022:145).

To enrich the understanding, we can combine the explanations from Margono and Arikunto as they both cited in Radjab and Jam'an (2017:100). According to Margono (2004:118), population encompasses all data within a specific space and time of study, meaning it focuses on the data characteristics rather than the human subjects. While Arikunto (2002:108) explains that population is the entirety of subjects in research, which can include not only people but also animals, plants, symptoms, or events, as long as they meet the defined characteristics for that study.

The research population for this study consists of consumers in Indonesia who have the purchasing power to buy electric vehicles (EVs). These consumers are typically individuals with a higher income level, sufficient to afford the relatively higher upfront costs of EVs compared to conventional vehicles. The population includes a diverse group of potential buyers, ranging from young professionals and middle-aged individuals to senior citizens, all of whom are interested in emerging transportation technology. This group is particularly relevant as they represent the segment of the market most likely to consider purchasing an EV due to their financial capacity, environmental awareness, and areas with potential EV charging accessibility.

3.3.2. Sample

In quantitative research, a sample is a portion of the population that shares the same characteristics as the larger group. When the population is too large to study in its entirety—often due to limitations in budget, time, or resources—a sample can be used to represent the population. The findings from the sample are expected to apply to the entire population. However, to ensure the results are valid, the sample must accurately represent the population. If the sample is not representative, the conclusions drawn may be misleading or biased, limiting the generalizability of the results. This could result in inaccurate predictions or flawed insights about the population as a whole, potentially impacting the reliability and usefulness of the research findings. (Sugiyono, 2022:146)

The sample for this research will be drawn from the larger population of consumers with the financial capability to purchase EVs across different income levels and geographic locations within Indonesia. To ensure the sample is representative, a stratified random sampling method will be employed. This involves dividing the population into different strata based on key characteristics such as age, income level, and geographic location. A random sample will then be taken from each stratum to ensure that all relevant segments of the population are adequately represented in the study. The sample size will be determined based on statistical guidelines to ensure sufficient power to detect significant relationships between the variables under investigation. This approach will help in obtaining accurate and generalizable insights into the factors influencing EV purchase intention among financially capable consumers in Indonesia.

According to Hair et al. (2022), determining the appropriate minimum sample size is essential for reliable data analysis in Partial Least Squares Structural Equation Modeling (PLS-SEM). Kline (2015) provides general guidelines for Structural Equation Modeling (SEM), suggesting that a sample size below 100 is considered small, and 100-200 is medium, while a sample size above 200 is considered large (Hair et al., 2022:305). These considerations guide researchers in planning sample sizes to ensure accurate and generalizable results.

This research involves six latent variables: Marketing Efforts, Facilitating Conditions, Perceived Benefits, Perceived Risks, Perceived Value, and Purchase Intention, meaning the minimum required respondents would be 10 x 6 = 60 respondents.

Since recommendations for sample size in PLS-SEM are based on the principles of ordinary least squares (OLS) regression, we can use more specific guidelines, like those from Cohen (1992 cited in Hair et al., 2014) in his statistical power analysis for multiple regression models as shown in the table below (Table 3.1). However, this approach is only valid if the measurement models meet quality standards, meaning that outer loadings should be above the common threshold of 0.70.

Table 5. Sample Size Recommendation a in PLS-SEM for statistical Power of 80% by Cohen*

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: * *as cited in Hair et al. (2014)*

Based on Cohen's guidelines (cited in Hair et al., 2014), the required sample size depends on the maximum number of arrows pointing at a construct (latent variable), the significance level, and the minimum R^2 value. This research involves six latent variables: Marketing Efforts, Facilitating Conditions, Perceived Benefits, Perceived Risks, Perceived Value, and Purchase Intention. Based on the research conceptual framework, the maximum number of arrows pointing at a construct is 3 (three), and the significance level is set at 5% with a minimum R^2 value. Referring to the table, with these parameters, the recommended sample size is 124 respondents to ensure sufficient statistical power of 80%. This sample size ensures that the analysis can produce reliable and meaningful results under the given conditions.

Structural Equation Modeling (SEM) is a statistical technique that analyzes complex relationships among multiple variables simultaneously. According to Hair et al. (2022), SEM integrates factor analysis and regression to evaluate the relationships between observed indicators and latent constructs, as well as the structural paths among those constructs. SEM can test theoretical models involving multiple dependent and independent variables at once, offering more comprehensive insights than traditional statistical methods.

There are two main approaches to SEM: Covariance-Based SEM (CB-SEM), which focuses on reproducing the data's covariance matrix, and Partial Least Squares SEM (PLS-SEM), which emphasizes maximizing the explained variance of the dependent variables. PLS-SEM is particularly useful in exploratory research or when the focus is on prediction rather than confirming established theory (Hair et al., 2022).

This method is widely applied in social sciences, marketing, and management research to assess complex models involving multiple variables. It helps researchers understand both direct and indirect effects, making it a powerful tool for testing theoretical frameworks.

The sampling method used in this study is non-probability sampling, where not all members of the population have an equal chance of being selected (Sugiyono, 2022). Non-probability sampling includes several types: 1) Systematic Sampling, 2) Quota Sampling, 3) Incidental Sampling, 4) Purposive Sampling, 5) Saturation Sampling, 6) Snowball Sampling, and 7) Census/Total Sampling. This research applies Purposive Sampling, where the sample is chosen intentionally based on specific criteria relevant to the study. This method focuses on selecting particular elements from the population to collect data that meets the study's objectives (Sugiyono, 2022).

3.4. Variable Operationalization

Operational variables refer to the specific, measurable characteristics or attributes that are used to represent abstract theoretical concepts in research studies. These variables are concrete and observable, allowing researchers to collect data and analyze relationships between variables (Ghauri, Grønhaug, and Strange 2020).

In this study, the operational variables include perceived benefits, perceived risks, facilitating condition, marketing efforts, EV perceived value, and EV purchase intention.

Table 6. Operationalization of Marketing Efforts

Variable	***Marketing Efforts***
Definition	Marketing effort is defined as the actions taken by EV dealers to promote and convince potential consumers about electric vehicles. These efforts include all activities that consumers (or respondents) can perceive and evaluate. To examine these efforts, we use the marketing mix approach, which looks at various promotional activities and strategies aimed at attracting and persuading consumers to consider electric vehicles. According to Kotler (2016), marketing mix refers to the set of tactical tools that a company uses to generate the desired response from its target market. In the EV market, the marketing mix consists of strategies to influence consumer demand for electric vehicles by addressing various factors that impact purchase decisions. It includes four key elements, known as the "four Ps": Product, which involves designing EVs with advanced features and modern technology; Price, which considers long-term savings through lower maintenance cost; Place, which ensures EVs and related services are accessible through well-developed sales networks and charging infrastructure; and Promotion, which focuses on raising awareness, offering incentives, and building trust in the new technology to encourage adoption (Koojaroenprasit and Pumpinyo, 2021).

Variable	*Marketing Efforts*		
	To improve marketing outcomes, companies should focus on enhancing the quality of after-sales service and attractive advertising campaigns. Additionally, expanding purchasing channels will make the buying process easier, and offering a wider variety of brands and EV models will give consumers more options to meet their needs (Wang et al., 2018)		
Measurement	***Product***		
	ME1	Modern design and technology advancement	KOOJ
	Price		
	ME2	Maintenance cost coverage	KOOJ
	Place		
	ME3	one-stop sales and service center	KOOJ
	ME4	many services center branches	KOOJ
	ME5	The EV purchase process is easy and fast	WANG
	Promotion		
	ME6	cash discount	KOOJ
	ME7	wall box (home charging) bonus	KOOJ
	ME8	quality assurance for the battery (lifetime-warranty)	KOOJ
	ME9	influencer endorsement through Social Media	INR
	ME10	Grand Car Exhibitions and Mall Exhibitions	INR
	ME11	The EV advertising and promotion are attractive	WANG
	Strategies		
	ME12	The EV after-sales service is guaranteed	WANG

Note : KOOJ (Koojaroenprasit and Pumpinyo, 2022); WANG (N. Wang, Tang, and Pan, 2018); INR (Input by Researcher)

Table 7. Operationalization of Facilitating Condition

Variable	***Facilitating Condition***		
Definition	‘Facilitating conditions’ can be defined as ‘the degree to which a person perceives that an underlying technical or organisational infrastructure exists to facilitate the utilisation of a given product or system’. (Venkatesh et al, 2003) In this research, ‘facilitating conditions’ will refer to consumers’ beliefs regarding the available support and resources to facilitate the utilisation of EVs, including the infrastructural distribution, total amount of operational charging stations (Wang et al, 2023), availability of sales facilities, incentives to increase electricity power, help center (Gunawan et al, 2022) and government tax incentives policy (Wang et al, 2018).		
Measurement	FC1	The public infrastructure for electric car is available	WANG1
	FC2	PLN offers easy installation of additional electricity meters for home EV charging (The electric car infrastructure at home is available)	INR
	FC3	The Indonesian government is actively setting up facilities for selling electric vehicles.	GUNA
	FC4	The Indonesian government is actively setting up public electric refueling facilities.	GUNA
	FC5	The Indonesian government is actively offering incentives to increase electric power for electric vehicle owners.	GUNA
	FC6	I think the subsidy policy for purchasing EVs is sufficient	WANG2
	FC7	Subsidy policy and preferential tax policies are important for me to purchase EVs	WANG2
	FC8	There is a help center that can be contacted in case of problems with electric vehicles.	GUNA

Note : WANG1 (D. Wang, Ozden, and Tsang, 2023); GUNA (Gunawan et al., 2022); WANG2 (S. Wang et al., 2018)

Table 8. Operationalization of Perceived Benefits

Variable	***Perceived Benefits***		
Definition	Perceived benefits refer to the advantages derived from the adoption of a product or service. The more benefits a person perceives in a product or service, the more value the person will derive from it. (Kim et al, 2018) In this research, perceived benefits will consist of perceived moneary/financial benefits, environmental benefits, psychological benefits (Kim et al, 2018 ;He et al, 2018; Hu et al, 2023) and perceived symbol (He et al, 2018)		
Measurement	***Financial***		
	PB1	EVs save fuel energy costs during driving	KIM, HE, HU
	PB2	Driving electric vehicles will give me other government incentives	HE
	PB3	Considering all (operational and maintenance) costs, driving electric vehicles is no more expensive than driving conventional cars	KIM, HE, HU
	Environment		
	PB4	EVs indicate care for the environment. (EVs help in responding to global warming via emissions reduction.)	KIM, HE, HU
	PB5	Driving an EV reduces the consumption of natural resources	HE
	Psychological / Enjoyment		
	PB6	Compared with conventional cars, EVs can make less noise while driving.	KIM, HU
	PB7	EVs give drivers pleasure and comfort.	KIM, HU
	Symbol		
	PB8	I would feel proud of driving an electric car	HE

Variable	*Perceived Benefits*		
	PB9	The electric car enhances my social status	HE

Note : KIM (Kim et al. 2018); HE (Xiuhong He, Zhan, and Hu, 2018); HU (Hu et al. 2023)

Table 9. Operationalization of Perceived Risks

Variable	***Perceived Risks***		
Definition	Perceived risks are the perceptions of the unexpected and uncertain results of purchasing a product or service. The higher the perception of the risks of a product or service, the lower the value perceived in that product or service. (Kim et al, 2018) Perceived risk is a multidimensional psychological factor. In this study, perceived risk divided into different types, such as technological and performance risk, financial risk, physical safety risk (Kim et al, 2018 ;He et al, 2018; Hu et al, 2023), social risk and time risk (Gunawan et al, 2022)		
Measurement	PR1	The costs of purchase and batteries reduce the attractiveness of EVs compared to conventional vehicles.	KIM, HU
	PR2	EV might cause an increase in the electrical load at home	GUNA
	PR3	EV's selling price may drop drastically in the future	GUNA
	PR4	EV's driving range is shorter than non-EV	KIM, HU
	PR5	EV's charging times is longer than refueling in conventional cars	KIM, HU, GUNA
	PR6	EVs driver's expectations of charging infrastructure	KIM, GUNA
	PR7	The inaudible sound of an electric vehicle's engine can increase the risk of an accident.	GUNA
	PR8	Electric vehicle batteries have the potential to explode while charging	GUNA

Variable	*Perceived Risks*		
	PR9	Electric vehicles may experience a power failure (turn off) during a flood	GUNA

Note : KIM (Kim et al. 2018); HE (Xiuhong He, Zhan, and Hu, 2018); HU (Hu et al. 2023); GUNA (Gunawan et al, 2022)

Table 10. Operationalization of Perceived Value

Variable	*Consumers Perceived Value*		
Definition	Consumers' perceived value refers to the overall assessment of the utility derived from a product or service, based on their perceptions of the benefits and risks associated with it. It has been emphasized that consumers make value judgments by weighing the positive aspects (benefits) against potential downsides (risks) of the product, which influences their purchase intentions. (Hu et al, 2023). This assessment takes into account various values dimension obtained from purchasing and using the product. In this research, perceived value represents the financial, emotional, social, environmental and performance values aquired by consumers when buying and adopting EVs. (Kim et al, 2018; Hu et al, 2023)		
Measurement	PV1	Compared to the fee that I need to pay, EVs offer value for money.	KIM
	PV2	EVs are considered to be a good buy	KIM
	PV3	Overall, EVs deliver me good value.	KIM
	PV4	If I buy and drive an EV, I can acquire environmental value because it does not emit exhaust gas.	HU
	PV5	EVs use emerging technologies that excite me.	HU

Note : KIM (Kim et al. 2018); HU (Hu et al. 2023)

Table 11. Operationalization of Purchase Intention

Variable	***Purchase Intention***		
Definition	Electric Vehicle (EV) Purchase Intention refers to the likelihood that a consumer will decide to buy an electric vehicle in the future. Within the framework of Consumer Perceived Value Theory, this intention is significantly influenced by the perceived value that consumers associate with electric vehicles. Perceived value encompasses the overall assessment of the benefits and costs associated with owning an EV, including functional, emotional, and social dimensions (Kim et al., 2018; Xiuhong He, Zhan, and Hu, 2018; Hu et al., 2023; D. Wang, Ozden, and Tsang, 2023).		
Measurement	PI1	I intend to buy an EV in the near future.	KIM, HE, HU, WANG
	PI2	If I replace my car, I will consider an EV first	KIM, HE, HU, WANG
	PI3	I recommend that others buy an EV.	KIM, HU, WANG
	PI4	I expect to drive an electric car in the near future	HE, WANG

Note : KIM (Kim et al. 2018); HE (Xiuhong He, Zhan, and Hu, 2018); HU (Hu et al. 2023); WANG (D. Wang, Ozden, and Tsang, 2023).

By operationalizing these variables, the research aims to quantitatively analyze the factors influencing EV purchase intention in Indonesia, providing clear insights into consumer behavior and preferences.

3.5. Data Collection Method

Data collection method refers to the process of gathering relevant information and data for research purposes. It involves selecting appropriate techniques and tools to collect data that will help answer research questions or test hypotheses (J. Bell and Waters, 2018). The methods of data collection can vary depending on the research design, objectives, and the type of data needed. Common data collection methods include surveys, interviews, observations, and experiments (Ghauri, Grønhaug, and Strange 2020). Data collection is a critical step in the research process, as it provides the foundation for analyzing and interpreting research findings.

The primary data collection method for this research is the use of structured questionnaires. This method involves designing a comprehensive survey that will be distributed to a representative sample of potential electric vehicle (EV) buyers in Indonesia. The questionnaire will include a variety of questions aimed at capturing data on the key operational variables of the study: perceived benefits, perceived risks, facilitating condition, marketing efforts, EV perceived value, and EV purchase intention.

The primary data collection method involves administering structured questionnaires to a representative sample of potential EV buyers in Indonesia. The questionnaire is designed to capture data on respondents' perceptions of the benefits and risks associated with EVs, the influence of facilitating condition, and the impact of marketing efforts. Additionally, it measures the perceived value of EVs and the respondents' purchase intentions. This quantitative data will be analyzed using statistical techniques, such as regression analysis, to test the proposed hypotheses and determine the strength and direction of the relationships between the variables.

The survey will use a combination of closed-ended and Likert-scale questions to ensure that the responses are both quantifiable and easy to analyze. Closed-ended questions will provide specific options for respondents to choose from, making it easier to categorize and quantify their answers. Likert-scale questions will allow respondents to express the degree of their agreement or disagreement with various statements, providing a nuanced understanding of their perceptions and attitudes.

A Likert scale is a widely used tool in quantitative research to measure attitudes, perceptions, or behaviors by asking respondents to express their level of agreement or disagreement with a given statement. It helps convert subjective opinions into numerical data, making it easier to analyze relationships between variables. The scale typically ranges from strongly agree to strongly disagree and allows researchers to understand the intensity of respondents' views (Walliman, 2011:113).

When using Likert scales in PLS-SEM studies, such as those involving consumer adoption of electric vehicles (EVs), the number of scale points can significantly impact the reliability and precision of the results. According to Hair (2019), five-point and seven-point scales are commonly used. A five-point scale offers simplicity, making it easier for respondents to answer, which can improve response rates and reduce fatigue. On the other hand, a seven-point scale captures finer differences in attitudes and provides more detailed data, enhancing reliability (Hair et al., 2022:48)

This research use a five-point Likert scale. This choice ensures that the questions remain straightforward and easy to answer, which is especially important when the study targets a broad audience. A five-point scale also offers sufficient variability for analysis while minimizing cognitive load on respondents, which can lead to more consistent and reliable data.

The questionnaires will be distributed online and in person to ensure a wide reach and higher response rate. Online distribution will leverage email lists, social media platforms, and EV forums, while in-person distribution will target locations such as car dealerships, EV charging stations, and public events related to sustainability and technology. This mixed-method approach will help in collecting a diverse and comprehensive set of data from different segments of the target population.

By employing structured questionnaires as the data collection method, the research aims to gather reliable and detailed information on the factors influencing EV purchase intention in Indonesia. This data will then be analyzed to test the proposed hypotheses and provide actionable insights for stakeholders in the EV market.

3.6. Data Analysis Method

Data analysis methods are critical processes in research that involve examining, interpreting, and making sense of the data collected during a study (Ghauri, Grønhaug, and Strange, 2020). Data analysis is essential to choose the appropriate method of analysis based on the research objectives and the nature of the data. (Mukherjee, 2020). These methods encompass a range of techniques and procedures used to analyze data, identify patterns, relationships, and trends, and draw meaningful conclusions based on empirical evidence. Data analysis allows researchers to uncover insights, test hypotheses, and address research questions effectively (Ghauri, Grønhaug, and Strange, 2020).

The data analysis method for this research involves using statistical techniques to examine the relationships between the factors influencing the purchase intention of electric vehicles (EVs) in Indonesia. After collecting the survey responses, the data will be input into a statistical software program like SmartPLS, SPSS or R. First, descriptive statistics will be calculated to summarize the basic features of the data, such as averages, frequencies, and standard deviations. This step helps in understanding the general trends and demographic characteristics of the respondents.

Next, inferential statistics will be used to test the research hypotheses. Multiple regression analysis will be conducted to determine how the independent variables (perceived benefits, perceived risks, facilitating condition, and marketing efforts) affect the dependent variables (EV perceived value and EV purchase intention). This analysis will help identify the strength and direction of the relationships between these factors. Additionally, structural equation modeling (SEM) may be used to further explore the complex interactions and causal relationships between the variables. This comprehensive approach ensures that the research findings are robust and provide valuable insights into what drives EV purchase intentions in Indonesia.

3.6.1. Measurement Model Analysis (Instrument Test)

Measurement Model Analysis, also known as an Instrument Test, is conducted to verify the reliability and validity of measurement tools such as questionnaires. This process ensures that the indicators accurately represent the variables being measured, contributing to the overall credibility of the research. According to Hair et al. (2017, p. 115), measurement model analysis confirms that observed variables adequately reflect the latent constructs they are intended to measure. Validity ensures that the instrument measures what it is supposed to, while reliability guarantees consistency across repeated measurements (Hair et al., 2019:135). In this study, instrument testing is carried out through a pretest to evaluate the measurement tool before it is applied in the main test. The pretest helps identify weak or low-performing indicators, allowing for refinement and adjustments to improve accuracy and reliability. By conducting this initial analysis, researchers can enhance the quality of the instrument, ensuring the robustness of the structural model and increasing confidence in the final research findings (Sarstedt, Ringle, and Hair, 2021).

3.6.1.1. Validity Test

Validity testing is a crucial step in assessing whether a measurement tool accurately reflects the construct it aims to measure. Validity ensures that the observed indicators truly represent the theoretical concept, thus supporting the accuracy of research findings (Hair et al., 2019:115). Proper validity testing enhances the credibility of the model, ensuring that each variable is measured precisely and consistently (Sarstedt et al., 2021:84).

An individual reflective measure is considered strong if it has a correlation greater than 0.7 with the construct it is intended to measure. However, for exploratory research, an Outer Loading value of 0.6 is generally accepted as adequate (Yana et al., 2015). This aligns with recommendations from Hair et al. (2017), who suggest that in exploratory studies, loading values between 0.6 and 0.7 can be acceptable, especially when the research is still in its early stages and aims to explore relationships (Hair et al., 2017:131). Using this guideline helps ensure that the indicators reasonably reflect the constructs while maintaining flexibility for studies focused on exploration.

3.6.1.2. Reliability Test

A reliability test is needed to verify whether the items used in a research instrument provide consistent results when applied multiple times to measure the same phenomenon (Putka and Sackett, 2010). One common method for testing reliability is using Cronbach's Alpha, which evaluates the internal consistency of the items. According to Hair et al. (2019), the results of Cronbach's Alpha are grouped into five categories to determine the reliability level. These categories help researchers assess whether the items are sufficiently reliable for use in research (Hair et al., 2017:123). Consistent and reliable measurements are essential to ensure the accuracy and trustworthiness of the findings.

Table 12. Cronbach's Alpha Reliability Test

Scale	Description
0.81 – 1.00	Very Reliable
0.61 – 0.80	Reliable
0.42 – 0.60	Moderately Reliable
0.21 – 0.41	Not Reliable
0.00 – 0.20	Very Unreliable

Source: Hair et al., 2017

If each variable shows a Cronbach's Alpha value greater than 0.7, the study is considered to have high reliability (Hair et al., 2017). These categories help researchers assess whether the items are sufficiently reliable for use in research (Hair et al., 2017:123).

3.6.2. Outer Model (Measurement Model)

To confirm whether the data model is valid and reliable for use, an outer model analysis is conducted (Hussein, 2015). This process involves analyzing latent variables and their indicators, specifying their relationships within the model to ensure accurate measurement. In this study, the outer model analysis will be applied during the main test data processing stage to verify that the refined measurement tools from the pretest phase effectively capture the intended constructs. This ensures that only reliable and valid indicators contribute to the final analysis, enhancing the accuracy and robustness of the research findings. Several key indicators are used to evaluate the outer model:

1. **Convergent Validity**: This measures the correlation between construct scores and component scores, evaluated using the Standardized Loading Factor. A high outer loading, with a value greater than 0.7, indicates strong correlation between the measurement indicator and the construct being measured (Hair et al., 2019). However, outer loading values between 0.5 and 0.6 are considered acceptable for exploratory research (Chin, 1998).

2. **Discriminant Validity**: This assesses how distinct a construct is from others in the model. It is evaluated using cross-loading, where indicators should correlate more strongly with their own construct than with others. Another method is the Average Variance Extracted (AVE), which compares the square root of each construct's AVE with the correlations between constructs (Sarstedt et al., 2021). The Heterotrait-Heteromethod Ratio (HTMT) is another discriminant validity metric, where a value below 0.90 is recommended for structural models (Henseler et al., 2015; Hair et al., 2017). Fornell and Larcker's criterion (1981) provides an additional approach, suggesting that the shared variance between constructs should not exceed the AVE of each construct (Hair et al., 2022).

3. **Composite Reliability**: This evaluates the reliability of a construct by assessing the consistency of latent variable coefficients. Composite reliability is measured through

internal consistency and Cronbach's Alpha, with values above 0.70 indicating high reliability (Hair et al., 2019).

4. **Cronbach's Alpha**: This reliability test complements composite reliability by ensuring consistent findings. According to Hair et al. (2010), the results of Cronbach's Alpha are grouped into five categories to determine the reliability level as shown in Table 3.7 above. If each variable shows a Cronbach's Alpha value greater than 0.7, the study is considered to have high reliability (Hair et al., 2017). Consistent and reliable measurements are essential to ensure the accuracy and trustworthiness of the findings.

These methods ensure that the model is both valid and reliable, enabling accurate and meaningful analysis.

3.6.3. Inner Model (Structural Model)

Before testing the inner model, a multicollinearity test is conducted to ensure that the latent variables in the model are not highly correlated indicating no multicollinearity (Hair et al., 2014). After confirming that there is no multicollinearity, the inner model test is performed. The inner model is analyzed in three stages: 1) R^2 Value, 2) Effect Size (f^2), and 3) Q^2 Value (Hair et al., 2014).

3.6.3.1. Multicollinearity Test

Multicollinearity testing is a statistical technique used to check if there is a high correlation between two or more independent variables in a regression model. Identifying multicollinearity is important because it can affect the stability and accuracy of the regression results. The primary goal of multicollinearity testing is to ensure that the regression model produces reliable and accurate estimates. If strong correlations between independent variables are not addressed, it can lead to biased parameter estimates and misinterpretation of the analysis. This test also improves the predictive quality of the model by confirming that each independent variable makes a unique contribution to the dependent variable.

To detect multicollinearity, several statistical methods can be used. One common approach is calculating the Variance Inflation Factor (VIF) for each independent variable, where when the VIF value is between 0.2 and 5, it indicates no multicollinearity (Hair et al., 2014).

3.6.3.2. Inner Model Test

In the theory-based substantive method, the Inner Relation, Structural Model, and Substantive Theory are used to describe the relationships between latent variables. When evaluating the inner model using Partial Least Squares (PLS), several tests are conducted:

1. **f-Square (Effect Size)**: This test assesses whether there is a significant relationship between variables. An f-Square value of 0.02 is considered small, 0.15 is moderate, and 0.35 is large. Values below 0.02 are disregarded (Hair et al., 2017).

2. **R-Square**: This statistic measures the extent to which variations in an endogenous variable can be explained by other exogenous or endogenous variables in the model. Changes in the R-square value are examined to determine whether specific independent latent variables significantly affect dependent latent variables. According to Chin (1998), R-square values are interpreted as 0.19 (low effect), 0.33 (moderate effect), and 0.66 (high effect).

3. **Q-Square (Predictive Relevance)**: This metric evaluates how well the model and its parameter estimates predict observed values. It complements the R-square value by measuring the predictive accuracy of the model. Q-square values are interpreted as 0 (low relevance), 0.25 (moderate relevance), and 0.50 (high relevance) (Hair et al., 2019).

These tests help ensure the structural model is well-defined and accurately explains the relationships and predictive capabilities within the PLS model.

3.6.4. Hypothesis Test

The probability value (p-value) and t-statistic are used to evaluate hypothesis testing results. The t-statistic, often referred to as the critical value, is set at 1.96 for a 95% confidence interval, with a p-value threshold of <0.05. Therefore, the criteria for accepting or rejecting a hypothesis are as follows: if the t-statistic is greater than 1.96 and the p-value is less than 0.05, the hypothesis is considered significant (Hair et al., 2019).

3.6.5. Multigroup Analysis

Multi-Group Analysis (MGA) represents a sophisticated multi-sample technique designed to compare data analysis across different datasets that reflect varying characteristics between two or more groups (Hair et al., 2022). This methodological approach enables researchers to identify meaningful differences between groups by analyzing how various conditions or variables influence outcomes, particularly when participants originate from diverse backgrounds or possess distinct characteristics. The application of MGA is especially pertinent in understanding consumer behavior, as psychological and socio-demographic factors significantly influence individual decision-making processes and behavioral patterns (Slabá, 2020).

The implementation of MGA in this study is particularly crucial given Indonesia's diverse demographic, geographic, and economic landscape, which substantially impacts consumer behavior and decision-making processes regarding electric vehicle (EV) adoption. Previous research has demonstrated that factors such as perceived environmental benefits, financial considerations, and technological awareness are frequently moderated by demographic variables including income level, age, and geographic location (Gunawan et al., 2022:5; Hu et al., 2023:3). This study employs MGA to evaluate the impact of several key variables: Facilitating Conditions, Marketing Efforts, Perceived Benefits, and Perceived Risks on Perceived Value and Purchase Intention, analyzing these relationships across different groups based on gender, age, socio-economic status (SES), and understanding of electric vehicles.

The heterogeneity in consumer behavior across distinct groups represents a central phenomenon in this investigation. Research has shown that urban consumers often prioritize environmental concerns and advanced EV technology due to greater exposure to sustainability campaigns and infrastructure, while rural consumers typically focus more on price value and operational convenience due to limited charging facilities and economic constraints (Dutta & Hwang, 2021:4). These variations are particularly evident in the Indonesian context, where financial disparities and infrastructure availability differ significantly across regions. For instance, price sensitivity and perceived financial risk demonstrate stronger effects on EV adoption among lower-income groups, while environmental awareness plays a more substantial role for higher-income segments (Gunawan et al., 2022:6). Similarly, environmental perceptions have shown greater impact in urban areas compared to rural regions, where practical and economic considerations take precedence (Wang et al., 2018:10).

This methodological approach aligns with recent research emphasizing the importance of tailored strategies for different consumer segments. Understanding these subgroup differences proves critical for developing inclusive policies that promote sustainable consumption (Gunawan et al., 2022:8). Through MGA, this study aims to provide valuable insights for policymakers and marketers, enabling them to develop more effective, targeted strategies for increasing EV adoption rates across different consumer segments in Indonesia.