

**FACTORS INFLUENCING ELECTRIC VEHICLE PURCHASE
INTENTION IN DKI JAKARTA USING
EXTENDED THEORY OF PLANNED BEHAVIOR (TPB)**



Thesis

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**Factors Influencing the Purchase Decision of
Electric Vehicles in DKI Jakarta**

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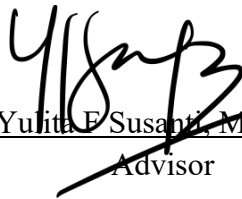


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This thesis is a presentation of my original research work. Whatever contributions others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgement of collaborative research and discussions.

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A handwritten signature in blue ink is written over a 10000 Indonesian postage stamp. The stamp features the Garuda Pancasila emblem and the text '10000', 'METERAI TEMBEL', and the serial number '8758CAOX24435532'.

Ali Alhabsyi

ABSTRACT

Indonesia has set a target of two million electric vehicles (EVs) on the road by 2030 and has supported it with incentives including a reduction in Value Added Tax (VAT) from 11% to 1% and exemptions from import duty. Uptake nevertheless remains modest: EVs accounted for only 2.92% of the national automotive market in the second quarter of 2024, even as consumer interest in EVs in DKI Jakarta rose by 104.13% over the same period. This gap between rising interest and actual purchasing is the problem the study addresses. Drawing on an extended Theory of Planned Behavior (TPB), the research examines how attitude toward electric vehicles, subjective norms, perceived behavioral control, environmental concern, and financial factors affect EV purchase intention in DKI Jakarta. Data were collected through an online questionnaire completed by 197 prospective EV buyers selected by purposive sampling, and analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. Four of the five hypotheses were supported. Attitude toward electric vehicles was the strongest predictor of purchase intention, followed by perceived behavioral control, financial factors, and subjective norms. Environmental concern had no significant effect. Together the five constructs explained 70.0% of the variance in purchase intention ($R^2 = 0.700$). The results indicate that environmental appeals on their own are unlikely to shift buying behaviour in Jakarta, and that attitude formation, financial accessibility, perceived control over ownership, and social influence carry considerably more weight.

Keywords: Electric vehicle adoption, Purchase intention, Theory of Planned Behavior, Consumer behavior, DKI Jakarta

TABLE OF CONTENTS

CERTIFICATE OF APPROVAL.....	2
NON-PLAGIARISM DECLARATION FORM.....	3
ABSTRACT.....	4
TABLE OF CONTENTS.....	5
LIST OF TABLES.....	9
LIST OF FIGURES.....	10
CHAPTER 1 INTRODUCTION.....	11
1.1 Background.....	11
1.2 Research Problem.....	16
1.3 Research Objectives.....	17
1.4 Research Benefits.....	17
1. Academic Benefits.....	17
2. Practical Benefits.....	17
1.5 Research Structure.....	18
CHAPTER 2 LITERATURE REVIEW.....	20
2.1 Theoretical Review.....	20
2.1.1 Theory of Planned Behavior (TPB).....	20
2.1.2 Application of TPB to Electric Vehicle Adoption.....	23

2.2	Hypothesis Development.....	26
2.2.1	The Effect of Attitude Toward Electric Vehicles on Purchase Intention.....	26
2.2.2	The Effect of Subjective Norms on Electric Vehicle Purchase Intention.....	27
2.2.3	The Effect of Perceived Behavioral Control on Electric Vehicle Purchase Intention.....	28
2.2.4	The Effect of Environmental Concern on Electric Vehicle Purchase Intention.....	29
2.2.5	The Effect of Financial Factors on Electric Vehicle Purchase Intention.....	30
2.3	Conceptual Framework.....	31
CHAPTER 3 METHODOLOGY.....		33
3.1	Types of Research.....	33
3.2	Research Location.....	33
3.3	Population and Sample.....	33
3.4	Data Sources and Types.....	34
3.5	Data Collection Method.....	34
3.6	Variables and Indicators.....	35
3.7	Data Analysis Techniques.....	38
3.7.1	Instrument Testing.....	38

3.7.1.1	Validity Test.....	38
3.7.1.2	Reliability Test.....	39
3.7.2	Classical Assumption Test.....	39
3.7.2.1	Multicollinearity Test.....	39
3.7.3	Descriptive Statistics.....	40
3.7.4	PLS-SEM Analysis.....	40
3.7.5	SEM-PLS Evaluation Criteria.....	41
3.7.6	Hypothesis Testing.....	42
CHAPTER 4	DATA ANALYSIS.....	44
4.1	Research Description.....	44
4.1.1	Respondent Overview.....	44
4.1.2	Instrument Validity and Reliability.....	46
4.1.3	Indicator Loadings.....	47
4.1.4	Internal Consistency Reliability.....	53
4.1.5	Convergent Validity.....	53
4.1.6	Discriminant Validity.....	54
4.1.7	Collinearity Assessment.....	56
4.2	Structural Model Evaluation and Hypothesis Test.....	57
4.2.1	Path Coefficient.....	58

4.2.2	Coefficient of Determination (R^2).....	59
4.2.3	The Effect Size (f^2).....	60
4.2.4	Hypothesis Testing.....	61
4.3	Discussion on Findings.....	63
4.3.1	Influence of Attitude Toward Electric Vehicles on Purchase Intention.....	64
4.3.2	Influence of Environmental Concern on Purchase Intention.....	64
4.3.3	Influence of Financial Factors on Purchase Intention.....	64
4.3.4	Influence of Perceived Behavioral Control on Purchase Intention	65
4.3.5	Influence of Subjective Norms on Purchase Intention.....	65
4.3.6	Implications for the Electric Vehicle Market in DKI Jakarta.....	65
CHAPTER 5 CONCLUSION AND RECOMMENDATIONS.....		66
5.1	Introduction.....	66
5.2	Conclusion.....	66
5.3	Research Limitations.....	67
5.4	Suggestions.....	67
REFERENCES.....		69
APPENDIX: RESEARCH QUESTIONNAIRE.....		90
Section A: Screening Questions.....		90
Section B: Main Survey.....		91
Section C: Demographics.....		94
Questionnaire Summary.....		94
Scale Sources and Reliability Expectations.....		94

LIST OF TABLES

Table 1.1	Consumer Segmentation and Demographic Characteristics of Indonesian Electric Vehicles.....	12
Table 3.1	Operational Variable Definitions and Measurement Framework.....	36
Table 3.2	SEM-PLS Evaluation Criteria.....	42
Table 4.1	Respondent Characteristics Based on Gender.....	44
Table 4.2	Respondent Characteristics Based on Age.....	45
Table 4.3	Respondent Characteristics Based on Educational Level.....	45
Table 4.4	Respondent Characteristics Based on Monthly Income.....	46
Table 4.5	Attitude Toward Electric Vehicles Outer Loadings.....	49
Table 4.6	Subjective Norms Outer Loadings.....	49
Table 4.7	Perceived Behavioral Control Outer Loadings.....	50
Table 4.8	Environmental Concern Outer Loadings.....	50
Table 4.9	Financial Factors Outer Loadings.....	51
Table 4.10	Purchase Intention Outer Loadings.....	52
Table 4.11	Reliability Test Result.....	53
Table 4.12	Convergent Validity Test Result.....	54
Table 4.13	Fornell-Larcker Criterion Analysis.....	55
Table 4.14	Cross-Loading Test.....	55
Table 4.15	Collinearity Results.....	56
Table 4.16	Path Coefficient Results.....	58
Table 4.17	R ² Test Result.....	59
Table 4.17	f ² Test Result.....	60
Table 4.18	Path Coefficients – Direct Effect.....	61

LIST OF FIGURES

Figure 1.1	Purchase Motivations by Consumer Segment.....	13
Figure 1.2	Adoption Barriers by Consumer Segment.....	14
Figure 2.1	Conceptual Framework.....	31
Figure 4.1	The Path Model – Initial Version (PLS Algorithm Result).....	47
Figure 4.2	Initial Validity Test.....	48

CHAPTER 1

INTRODUCTION

1.1 Background

Around the world, electric vehicles are increasingly regarded as one of the more workable responses to environmental pressure: they emit nothing from the tailpipe and reduce dependence on petroleum-based fuel (Yang et al., 2020). That advantage counts for even more in dense cities such as Jakarta, where pollution and carbon output already weigh on public health and the local environment. The numbers behind this shift speak for themselves. Worldwide EV sales reached about 17 million units in 2024, taking the technology's share of the market beyond 20% (IEA, 2025). China remains well ahead of everyone else, with EVs accounting for close to half of all cars sold there last year, but arguably the more interesting developments are happening elsewhere. In parts of Asia and Latin America, EV sales rose by over 60% during the same period. Southeast Asia moved in the same direction, with sales up nearly 50% and EVs now holding roughly 9% of the regional car market, a result driven mainly by Thailand and Vietnam (IEA, 2025). In short, EV adoption is no longer something on the horizon; it is already reshaping how people choose their cars.

For Indonesia the stakes are especially high. The country ranks among the world's larger carbon emitters, and transportation alone is responsible for roughly 27% of its total CO₂ output, which is why EVs now sit at the center of its environmental agenda (Maghfiroh et al., 2022). Policy, however, says little about who is actually buying these vehicles. Consumer segmentation data offers a sharper picture of the demographic patterns behind EV adoption in Indonesia, and these are summarized in Table 1.1.

**Table 1. 1 Consumer Segmentation and Demographic Characteristics
of Indonesian Electric Vehicles**

<i>Segment</i>	<i>(%)</i>	<i>Avg</i>	<i>Gender Majority</i>	<i>Primary Location</i>	<i>Daily Commute</i>	<i>Daily Commute Distance</i>
<i>EV Owners</i>	7%	42 years	60% Female	85% Large Cities	93%	31 km
<i>EV Prospects</i>	78%	40 years	51% Female	61% Large Cities	70%	23 km
<i>EV Sceptics</i>	15%	41 years	55% Male	37% Suburban	51%	23 km

Source: PwC eReadiness Indonesia Study 2024

Table 1.1 shows that current EV owners, the early adopters, make up 7% of the population. They average 42 years of age, are predominantly female (60%), and are concentrated heavily in large cities (85%). The biggest group by far is made up of EV prospects, who represent 78% of consumers and point to a sizeable untapped market. EV skeptics, at 15%, are more likely to live in suburban areas and to commute less intensively on a daily basis. Taken together, these patterns suggest that even though adoption is still limited, Indonesia has a strong base of potential customers for EVs to grow from.

The Indonesian government has signaled a firm commitment to electrification through Presidential Regulation No. 55 of 2019, which launched the Battery Electric Motor Vehicle Acceleration Program and set targets of 2 million electric cars and 12 million electric two-wheelers by 2030 (Christina et al., 2025). A set of economic incentives underpins the policy, including a cut in Value Added Tax (VAT) from 11% to 1% and exemptions from import duty on electric vehicles, both running through 2025. Yet despite all this, EV uptake in Indonesia remains modest. EVs represent just 1.47% of total automotive sales, well short of the government's 2025 target of 400,000 units (Falisa & Tricahyono, 2025). The gap between official targets and what the market has delivered suggests that policy support on its own may not be enough to move consumers toward electric vehicles, which makes it important to look closely at the factors that shape their purchase decisions.

Jakarta occupies a central place in Indonesia's EV story, largely because its charging infrastructure is more developed than anywhere else in the country. Roughly 1,100 of the nation's 1,500 EV charging stations are located in the capital,

making it the primary hub for electric mobility (Maghfiroh et al., 2022). The city government has added a layer of local support as well, exempting EVs from odd-even traffic restrictions and from ownership tax. These measures have reinforced Jakarta's standing as one of Indonesia's leading markets for electric cars (Christina et al., 2025).

Consumer interest has grown considerably too. When BYD entered the Indonesian market in 2024, for instance, it secured a 4.6% market share in short order. Interest in EVs within Jakarta rose by 104.13% in the second quarter of 2024, yet EVs still represented only 2.92% of the national automotive market over the same period (International Institute for Sustainable Development, 2025). These figures make clear that while curiosity about EVs is rising, actual adoption remains low. The mismatch between interest and buying behavior implies that consumers weigh many considerations before committing to an EV. Consumer purchase motivation data therefore offers a useful starting point for understanding why some people are ready to buy while others hold back, particularly in Jakarta. The main factors shaping consumer motivation are shown in Figure 1.1.

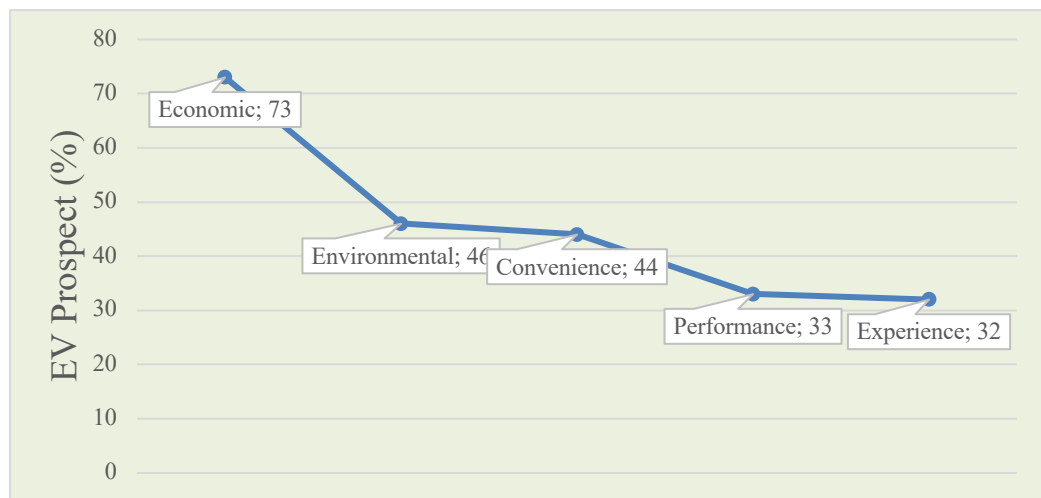


Figure 1. 1 Purchase Motivations by Consumer Segment

Source: *PwC eReadiness Indonesia Study 2024*

Figure 1.1 shows that financial considerations, above all fuel cost savings, are the leading motivation for buying an EV, cited by 73% of prospective consumers. Environmental benefits come second (46%), followed by convenience factors such as the ability to charge at home (44%), vehicle performance (33%), and driving experience (32%). While environmental awareness clearly plays a part, financial

and practical advantages remain the dominant drivers of consumer decision-making.

That said, earlier research offers conflicting evidence on the role of environmental, technological, and social influences. Christina et al. (2025) reported that environmental awareness significantly affects purchase intention, whereas Wulandari (2023) found environmental concern to be insignificant among Generation Z consumers in Jakarta. In much the same way, Saleh et al. (2024) and Sholikhah et al. (2024) reported differing levels of significance for technology acceptance factors.

Alongside these motivations, a number of obstacles continue to slow EV adoption. Figure 1.2 illustrates the main barriers.

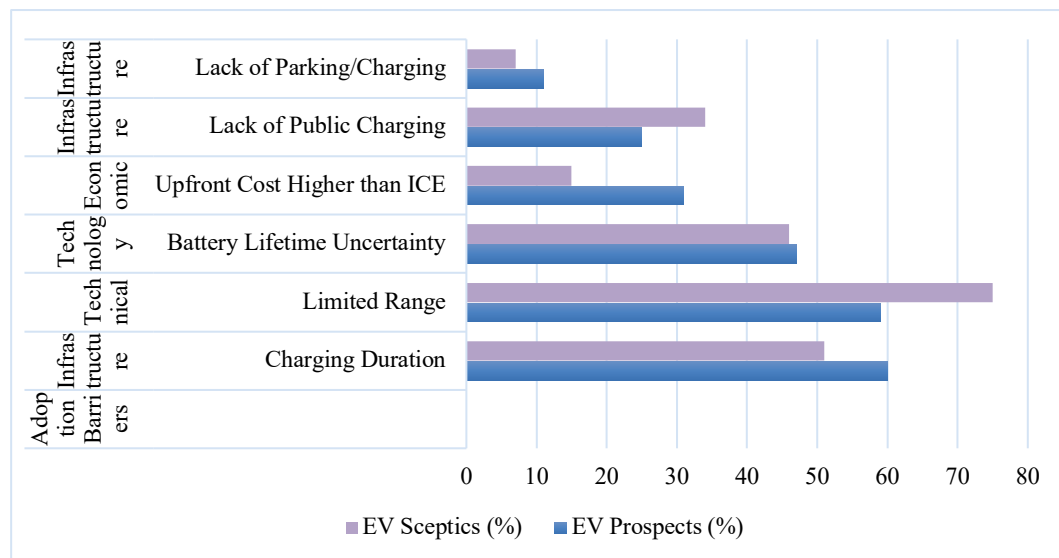


Figure 1. 2 Adoption Barriers by Consumer Segment

Source: *PwC eReadiness Indonesia Study 2024*

Figure 1.2 shows that limited infrastructure, price worries, and uncertainty about the technology remain the chief obstacles to EV adoption. Earlier research likewise identifies the availability of charging infrastructure as a major constraint on purchase decisions in Jakarta (Nurcahyo et al., 2023). Seen together, these barriers point to a fairly plain conclusion: without more dependable infrastructure and more competitive pricing, EV adoption is unlikely to gather much momentum.

Looking more closely at the segmentation data, consumers can be sorted into several behavioral personas: Tech Enthusiasts, Mainstream, Dreamers, Luxurious,

and Frugal buyers. Tech Enthusiasts and Dreamers together make up 58% of potential buyers, which underlines how much technological innovation and environmental positioning matter to any marketing strategy. It is also worth noting that satisfaction among current EV owners in Indonesia stands at 93%, with efficient charging, lower running costs, and everyday convenience cited as the main reasons.

Price nonetheless remains the decisive issue for most people. Roughly 78% of consumers rank affordability as their top priority, and about 27% of prospective buyers expect an EV to be priced under IDR 484 million, a clear signal of demand for cheaper models. On the infrastructure side, consumers appear comfortable with a charging time of around 32 minutes and expect an average driving range of about 370 kilometers.

With so many elements feeding into an EV purchase, a sound theoretical framework is needed to make sense of them. The theory of planned behavior (TPB) provides a useful starting point, explaining behavioral intention through three components: attitude, subjective norms, and perceived behavioral control (Ajzen, 2020). Meta-analytic evidence indicates that TPB explains roughly 39% of the variance in behavioral intention (Armitage & Conner, 2001). Research on EV adoption suggests, however, that the model performs better when it is extended with factors specific to the domain.

In Jakarta, attitudes toward EVs are influenced by exposure to charging infrastructure, government incentives, and environmental awareness. Subjective norms carry considerable weight given Indonesia's collectivistic culture and the strength of social influence within it (Refor et al., 2023). Perceived behavioral control, for its part, depends a great deal on how accessible infrastructure is and how supportive local policy turns out to be (Maghfiroh et al., 2022).

Environmental concern is relevant here as well, not least because of Jakarta's ongoing struggle with air pollution. Studies have shown that environmental awareness strengthens attitude, subjective norms, and perceived behavioral control alike in the context of EV adoption (Wang et al., 2016; Leksana et al., 2025). Finally, financial considerations remain a dominant influence in emerging markets,

where affordability and cost-benefit judgments weigh heavily on what consumers ultimately decide (Falisa & Tricahyono, 2025).

1.2 Research Problem

Knowing what drives the intention to buy an electric vehicle is essential if Indonesia's move toward sustainable transportation is to succeed. Although the government has introduced a broad range of incentives and policy frameworks to accelerate EV adoption, market penetration remains low. EVs account for only 1.47% of total automotive sales, far below the national target.

This matters most in DKI Jakarta, the center of both EV infrastructure development and policy implementation in Indonesia. The city hosts the majority of the country's charging stations and offers a range of local incentives that make EV ownership more attractive. Even with these favorable conditions and a large pool of potential customers, however, comparatively few people are converting their interest into an actual purchase.

Previous studies have examined a variety of factors behind EV adoption, from financial considerations and infrastructure readiness to environmental awareness and social influence. More often than not, though, these elements have been studied in isolation rather than combined into a single model capable of explaining EV purchase intention within Jakarta's particular urban setting. To address that gap, this study poses the following research questions:

1. How does attitude toward electric vehicles affect purchase intention in DKI Jakarta?
2. How do subjective norms affect electric vehicle purchase intention in DKI Jakarta?
3. How does perceived behavioral control affect electric vehicle purchase intention in DKI Jakarta?
4. How does environmental concern affect electric vehicle purchase intention in DKI Jakarta?

5. How do financial factors affect electric vehicle purchase intention in DKI Jakarta?

1.3 Research Objectives

1. To analyse how attitude toward electric vehicles affects consumer purchase intention in DKI Jakarta
2. To analyse how subjective norms affect electric vehicle purchase intention among consumers in DKI Jakarta
3. To analyse how perceived behavioral control affects consumer purchase intention for electric vehicles in DKI Jakarta
4. To analyse how environmental concern affects electric vehicle purchase intention among consumers in DKI Jakarta
5. To analyse how financial factors affect electric vehicle purchase intention among consumers in DKI Jakarta

1.4 Research Benefits

1. Academic Benefits

This study is intended to enrich consumer behavior theory, particularly as it relates to the acceptance of sustainable technology in emerging markets. By applying the Theory of Planned Behavior (TPB) to electric vehicle purchase decisions, it demonstrates how a behavioral framework can be combined with environmental and financial considerations to explain what shapes consumer choice.

2. Practical Benefits

In practical terms, the results should prove useful to several groups within the EV industry. For government bodies, the findings can inform the design and evaluation of policies, incentives, and infrastructure strategies aimed at raising EV adoption across Indonesia. For automotive manufacturers and EV companies, the study sheds light on consumer preferences, price sensitivity, and infrastructure expectations, all of which bear on product positioning and

marketing strategy. The findings may also be a helpful reference for investors, infrastructure developers, and urban planners working to build more sustainable transportation systems, in Jakarta and in other rapidly growing metropolitan areas.

1.5 Research Structure

To examine the factors shaping EV purchase decisions in DKI Jakarta in an orderly way, this thesis is arranged into the following chapters:

Chapter 1 – Introduction.

Lays out the background of the study, the problem statement, research questions, objectives, significance, and a review of earlier research. Together these establish the basis and rationale for the study.

Chapter 2 – Literature Review.

Reviews the theoretical foundation, focusing on the Theory of Planned Behavior and how it has been applied to EV adoption. It also surveys global and Indonesian adoption patterns, consumer behavior perspectives, and the policy context, before setting out the conceptual framework and hypotheses.

Chapter 3 – Research Methodology.

Explains the research design, population and sample, data collection method, operational definitions, measurement instruments, and analytical techniques. PLS-SEM is used to test the hypotheses and examine the relationships between variables.

Chapter 4 – Results and Analysis.

Presents the survey findings and statistical analysis, including descriptive statistics for respondents, evaluation of the measurement model, testing of the structural model, and the results of hypothesis testing.

Chapter 5 – Discussion.

Interprets the results against the literature review and conceptual framework, highlighting theoretical contributions, managerial implications, and what the findings mean for EV adoption in Jakarta.

Chapter 6 – Conclusion and Recommendations

Summarizes the main findings, sets out theoretical and practical contributions, and offers policy recommendations. It also notes the study's limitations and suggests directions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior, introduced by Ajzen (1991), continues to be one of the most widely used and thoroughly validated frameworks for explaining and predicting human behavior across many settings. As a psychological model, it provides a structured lens on the cognitive processes behind individual decisions, pinpointing the key psychological drivers of both behavioral intention and actual behavior (Ajzen, 2020). Its enduring appeal comes from a blend of simplicity, theoretical rigor, and strong predictive validity, qualities that make it particularly well suited to the study of complex consumer behavior.

TPB rests on the premise that people are, by and large, rational and that they draw systematically on the information available to them when forming intentions (Armitage & Conner, 2001). Behavioral intention is regarded as the most proximate predictor of behavior, capturing the motivational forces that determine how much effort someone is prepared to put into a given action. Meta-analytic evidence bears this out: TPB has been shown to account for about 27% of the variance in behavior and 39% of the variance in behavioral intention, a solid performance across a broad range of domains (Armitage & Conner, 2001).

This predictive capacity derives from three conceptually distinct antecedents of intention: attitude toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 2020). The three work in combination to shape intention, though the influence of each can vary with the situation and the population under study. Much of the theory's practical usefulness lies in this structure, because it identifies specific psychological constructs that interventions can target in order to change behavior.

Attitude toward the behavior refers to a person's overall appraisal of performing a given action, encompassing both cognitive and affective elements. It arises from beliefs about the likely outcomes of the action and from how the person values those outcomes (Ajzen, 2020). In research on technology adoption, attitude has consistently proven a strong predictor of intention, a reminder of how much personal evaluation matters when people decide. Cheng (2018), for instance, found that attitude significantly shaped students' intentions to adopt collaborative technology, and Yuriev et al. (2020) showed that positive attitudes toward environmental practices were strong predictors of pro-environmental intentions. The construct covers utilitarian judgments, such as perceived benefits and costs, along with hedonic ones, including satisfaction and emotional reactions to the behavior.

Subjective norms describe the social pressure a person perceives to engage in or refrain from a behavior, reflecting the influence of people whose opinions carry weight with them. The construct includes injunctive norms, meaning what others are believed to expect, and descriptive norms, meaning what others are believed to actually do (Ajzen, 2020). Social influence tends to be strongest where a behavior is highly visible or bound up with identity. Meta-analyses generally find subjective norms to be a weaker predictor than attitude or perceived behavioral control, though the picture shifts with culture. Armitage and Conner (2001) noted that normative influence varies across behavioral settings, and studies in collectivist societies often report stronger social effects, reflecting the greater weight placed on group harmony and conformity.

Perceived behavioral control (PBC) captures how easy or hard a person expects a behavior to be, based on the resources, opportunities, and capabilities they believe they have (Ajzen, 2020). It spans internal factors, such as knowledge, skill, and confidence, and external factors, such as access and the availability of resources. Within TPB, PBC affects both intention and actual behavior directly, especially when perceived control closely tracks real control. The research record consistently shows that intentions strengthen when people believe they have what they need to act. Armitage and Conner

(2001) confirmed that PBC adds significant explanatory power for both intention and behavior, over and above attitude and subjective norms.

Beneath these three constructs lies a belief structure: behavioral beliefs, normative beliefs, and control beliefs give rise to attitude, subjective norms, and PBC respectively (Ajzen, 2020). Such beliefs typically take shape through direct experience, observation of related behaviors, or information drawn from external sources. Research has also demonstrated that keeping measures of intention and behavior aligned on action, target, context, and time improves the accuracy of TPB models.

The predictive power of the theory has been confirmed across many behavioral domains. Armitage and Conner (2001) found that TPB explains about 31% of the variance in self-reported behavior and 21% in objectively measured behavior, a gap that shows how the choice of measurement can affect results. Even so, the evidence confirms that TPB is both robust and adaptable in a wide range of research settings.

While TPB provides a firm foundation, scholars have proposed extending it to improve its explanatory reach in particular contexts. Constructs such as past behavior, moral norms, personal norms, self-identity, and emotional factors have been added to capture influences the original model does not fully account for (Ajzen, 2020). Any extension, however, needs a solid theoretical and empirical basis to preserve conceptual consistency. Yuriev et al. (2020) report that adding environmental concern and moral norms to studies of environmental behavior has improved predictive validity, underscoring the part ethical considerations play in sustainable decision-making.

From a methodological standpoint, applying TPB requires careful attention to how measures are constructed and validated. Ajzen (2020) emphasizes that TPB questionnaires should be adapted to the particular behavior and population being studied so that they remain theoretically relevant and measure accurately. To examine the links between constructs while accounting for measurement error, more recent TPB studies have increasingly turned to advanced statistical techniques, particularly structural

equation modeling (Cheng, 2018). Partial least squares structural equation modeling (PLS-SEM) has become especially popular because it copes with complex behavioral models and suits studies with moderate sample sizes.

2.1.2 Application of TPB to Electric Vehicle Adoption

Applying the Theory of Planned Behavior to electric vehicle adoption illustrates how adaptable the theory is when it comes to explaining technology adoption in the transportation sector. Buying an EV is seldom a quick, one-off decision. It involves a real financial commitment, calls for changes to daily routines, and raises environmental questions in a way that a conventional car purchase usually does not. That combination is exactly why TPB fits so well here: the theory captures both the rational weighing of costs and benefits and the social pressures that shape how people decide.

TPB's wider track record in technology adoption research offers further support. It has been applied to a broad range of innovations, and its predictive performance has been consistently strong. Cheng (2018), for example, found that TPB predicted students' intentions to use collaborative tools about as well as the Technology Acceptance Model, and highlighted how much social influence entered into that decision. The same reasoning holds for EVs. They remain a conspicuous, socially charged purchase, and what peers think and do tends to shape how people view them and whether they eventually buy one.

Studies of EV adoption from other countries arrive at broadly the same conclusion. In India, Sharma and Shalender (2020) applied an extended TPB model to 326 consumers and found that attitude, subjective norm, perceived behavioral control, moral norm, and environmental concern all had a positive effect on adoption intention. Their findings are particularly relevant to developing markets, since they show that an extended TPB model can work well outside Western settings when the right contextual variables are included. Evidence from China follows a similar pattern, with TPB proving a dependable predictor of hybrid electric vehicle adoption. Wang et al. (2016) showed that attitude toward hybrid electric vehicles, subjective norm, and

perceived behavioral control partly mediate the effect of environmental concern on adoption intention, confirming that TPB has considerable explanatory power for environmentally motivated technology adoption.

Findings from Europe strengthen the case for applying TPB to EV adoption. In a Turkish study, Yeğin and Ikram (2022) expanded the TPB framework to incorporate environmental concern and green trust, and found that attitude, perceived behavioral control, environmental concern, and green trust all positively influenced EV purchase intention. Notably, subjective norms had a negative effect in their model, which serves as a reminder that the influence of social norms on consumer behavior can differ markedly from one context to another.

Work in emerging markets adds further perspective on how TPB applies to EV adoption. Low et al. (2025) studied EV adoption motivation using TPB with environmental concern as a mediating variable, and found significant positive relationships between attitude, perceived behavioral control, subjective norm, and EV purchasing behavior. Their findings help clarify what motivates EV adoption in markets where financial constraints are a real concern.

Research carried out in Indonesia provides insights that bear directly on this study. Refor et al. (2023) found that subjective norms, perceived behavioral control, environmental concern, and moral norms each had a significant effect on EV adoption intention among Indonesian consumers, while attitude did not. This result hints that cultural and contextual factors may be altering the relative weight of TPB constructs in the way Indonesian consumers reach their decisions.

Across numerous studies, attitude toward EVs stands out as a reliable predictor of adoption intention. Gayathiri and Ahamed (2025), for example, found that perceived EV benefits, confidence in the technology, and environmental consciousness all significantly influenced adoption intention among prospective buyers in India. More generally, the literature suggests that favorable attitudes toward EVs are shaped by perceptions of environmental gains, economic advantages, technological innovation, and

dependable performance. Such attitudes tend to form through direct experience with EV technology, exposure to positive product information, and an individual's own environmental values.

Subjective norms, by contrast, produce a more varied picture across cultural and market contexts. Some studies find a positive link between social influence and EV adoption intention, while others report weak or even negative effects. Javid et al. (2022) found that subjective norms, perceived behavioral control, and attitude significantly influenced EV purchase intention in Pakistan, with behavioral intention serving as a mediating variable. Differences in EV market maturity, cultural characteristics, and perceptions of the social status attached to EV ownership may account for the inconsistent findings across research settings.

Perceived behavioral control has consistently emerged as a significant driver of EV adoption intention, highlighting how much the availability of resources and perceived barriers shape decisions. He and Zhou (2022), for instance, found that perceived behavioral control significantly influenced EV purchase intention and that higher-income consumers were especially sensitive to control-related factors. In EV research, this construct typically encompasses judgments about financial affordability, knowledge and the ability to operate the vehicle, access to charging infrastructure, and how well an EV fits into everyday travel. These considerations carry even more weight in emerging markets, where gaps in infrastructure and resources create real obstacles to adoption.

In terms of method, current TPB research on EV adoption often relies on structural equation modeling to examine the intricate relationships among psychological constructs. Leksana et al. (2025) used SEM through SmartPLS to study how environmental concern influences attitudes and behavioral intentions toward EV adoption, and found that environmental concern significantly affects attitude, subjective norm, and perceived behavioral control.

The growing use of Partial Least Squares Structural Equation Modeling (PLS-SEM) in TPB-based EV research reflects its flexibility in

handling complex theoretical models and its robustness across varied sample characteristics. The method lets researchers evaluate measurement validity and structural relationships among TPB constructs at the same time, yielding a fuller understanding of behavioral decision-making.

Research also shows that TPB relationships in EV adoption differ across cultural and economic contexts. Studies in collectivist societies frequently report stronger effects for subjective norms, whereas research in individualistic cultures tends to emphasize attitudinal influences. Levels of economic development shape TPB patterns as well, since resource constraints in developing markets raise the importance of perceived behavioral control.

Thakur et al. (2023) found that attitude, subjective norms, and perceived trust significantly influenced EV adoption intention in Punjab, suggesting that trust-related factors may be a valuable contextual extension to TPB in certain cultural settings. The finding reinforces the case for adapting TPB to context when studying the adoption of emerging technologies.

Overall, the expanding body of TPB-based EV research provides strong theoretical and empirical grounds for investigating consumer adoption behavior in sustainable transportation. The continuing evolution of TPB applications underlines how important contextual variables, methodological rigor, and cultural adaptation are in explaining consumer decisions about electric vehicles.

2.2 Hypothesis Development

2.2.1 The Effect of Attitude Toward Electric Vehicles on Purchase Intention

Attitude toward electric vehicles reflects how favorably or unfavorably consumers regard the prospect of adopting EV technology. Within the Theory of Planned Behavior, attitude is considered one of the central determinants of behavioral intention and plays a major part in steering consumer decisions (Ajzen, 2020). Positive attitudes toward EVs generally grow out of perceptions of environmental benefit, technological advancement, and long-term operating efficiency.

Prior research has consistently found that favorable attitudes toward electric vehicles have a significant influence on adoption intention. In India, Sharma and Shalender (2020) reported that attitude toward EVs positively affected consumers' intention to adopt them. Similarly, Wang et al. (2016) found that positive evaluations of hybrid electric vehicles made consumers markedly more willing to embrace environmentally friendly transportation. Further work by Yeğın and Ikram (2022) and Low et al. (2025) confirms a significant positive relationship between attitude and EV purchase intention across several emerging markets. Gayathiri and Ahamed (2025) and Javid et al. (2022) add that perceived benefits, confidence in the technology, and environmental awareness all help to strengthen positive consumer attitudes toward EV adoption.

On this evidence, consumers who regard electric vehicles as beneficial, environmentally friendly, and technologically dependable tend to express stronger purchase intentions. The hypothesis can therefore be stated as follows:

H1: Attitude toward electric vehicles has a positive and significant effect on electric vehicle purchase intention.

2.2.2 The Effect of Subjective Norms on Electric Vehicle Purchase Intention

Subjective norms refer to the social pressure people experience from individuals or groups whose views matter to them, and to how that pressure shapes their behavioral choices. In the Theory of Planned Behavior, the construct reflects how strongly a person believes that significant others, including family, friends, colleagues, and society more broadly, would approve or disapprove of a particular behavior (Ajzen, 2020). In collectivistic cultures, this form of social influence often bears heavily on consumer decisions, especially where new and highly visible technologies such as electric vehicles are concerned.

A body of earlier research supports the link between subjective norms and the intention to adopt electric vehicles. Javid et al. (2022) reported that subjective norms significantly affected consumers' willingness to buy EVs in

Pakistan, and Thakur et al. (2023) showed that social approval positively shaped adoption intention among Indian consumers. In Indonesia, Refor et al. (2023) found that subjective norms significantly influenced consumers' intention to adopt EVs, highlighting the importance of social influence in the local context. Zhang et al. (2022) and Wang et al. (2016) offer further support, confirming a positive relationship between subjective norms and EV adoption intention across several Asian markets.

On this basis, consumers who sense positive support and encouragement from their social environment tend to develop stronger intentions to purchase electric vehicles. The hypothesis can therefore be stated as follows:

H2: Subjective norms have a positive and significant effect on electric vehicle purchase intention.

2.2.3 The Effect of Perceived Behavioral Control on Electric Vehicle Purchase Intention

Perceived behavioral control describes how capable consumers feel of performing a particular behavior, given their access to resources, knowledge, opportunities, and supporting infrastructure. In the Theory of Planned Behavior, this construct plays a central part in shaping behavioral intention and reflects a person's confidence in being able to carry the behavior through (Ajzen, 2020).

Empirical work has repeatedly shown that perceived behavioral control has a significant effect on the intention to adopt electric vehicles. Armitage and Conner (2001) found that it accounts for a meaningful share of the variance in behavioral intention across many contexts. In EV research specifically, Sharma and Shalender (2020) reported a positive effect on adoption intention among Indian consumers, and He and Zhou (2022) observed a significant influence on EV purchase intention in China. Studies by Refor et al. (2023) in Indonesia and Low et al. (2025) in Malaysia likewise confirm that consumers who feel greater control over, and access to, EV ownership tend to hold stronger purchase intentions. Leksana et al. (2025) and

Chukwuma (2023) provide further evidence, reporting similar positive relationships in the Philippines and Rwanda.

These findings indicate that consumers who feel they have adequate financial capacity, infrastructure access, and technological knowledge tend to show stronger intentions to adopt electric vehicles. The hypothesis can therefore be stated as follows:

H3: Perceived behavioral control has a positive and significant effect on electric vehicle purchase intention.

2.2.4 The Effect of Environmental Concern on Electric Vehicle

Purchase Intention

Environmental concern reflects how aware consumers are of environmental problems and how willing they are to contribute to environmental protection through responsible consumption. It is widely regarded as a key influence on pro-environmental behavior, including the adoption of green technologies such as electric vehicles.

Earlier studies indicate that environmental concern has a considerable effect on the intention to adopt EVs. Wang et al. (2016) found that it not only positively influenced consumers' intention to adopt hybrid electric vehicles but also strengthened the core psychological constructs of the TPB framework. Yeğın and Ikram (2022) reported a similar effect on EV purchase intention in Turkey. Leksana et al. (2025) went further, showing that environmental concern positively shaped consumers' attitudes, subjective norms, and perceived behavioral control in relation to EV adoption. Gayathiri and Ahamed (2025) and Refor et al. (2023) added to this evidence, confirming that environmental awareness positively influenced adoption intention in India and Indonesia respectively. Low et al. (2025) completed the picture by demonstrating that environmental concern plays a significant role in shaping EV adoption behavior across emerging markets.

On this evidence, consumers with greater environmental awareness and a stronger sense of environmental responsibility are more likely to express firm intentions to purchase electric vehicles. The hypothesis can therefore be stated as follows:

H4: Environmental concern has a positive and significant effect on electric vehicle purchase intention.

2.2.5 The Effect of Financial Factors on Electric Vehicle Purchase Intention

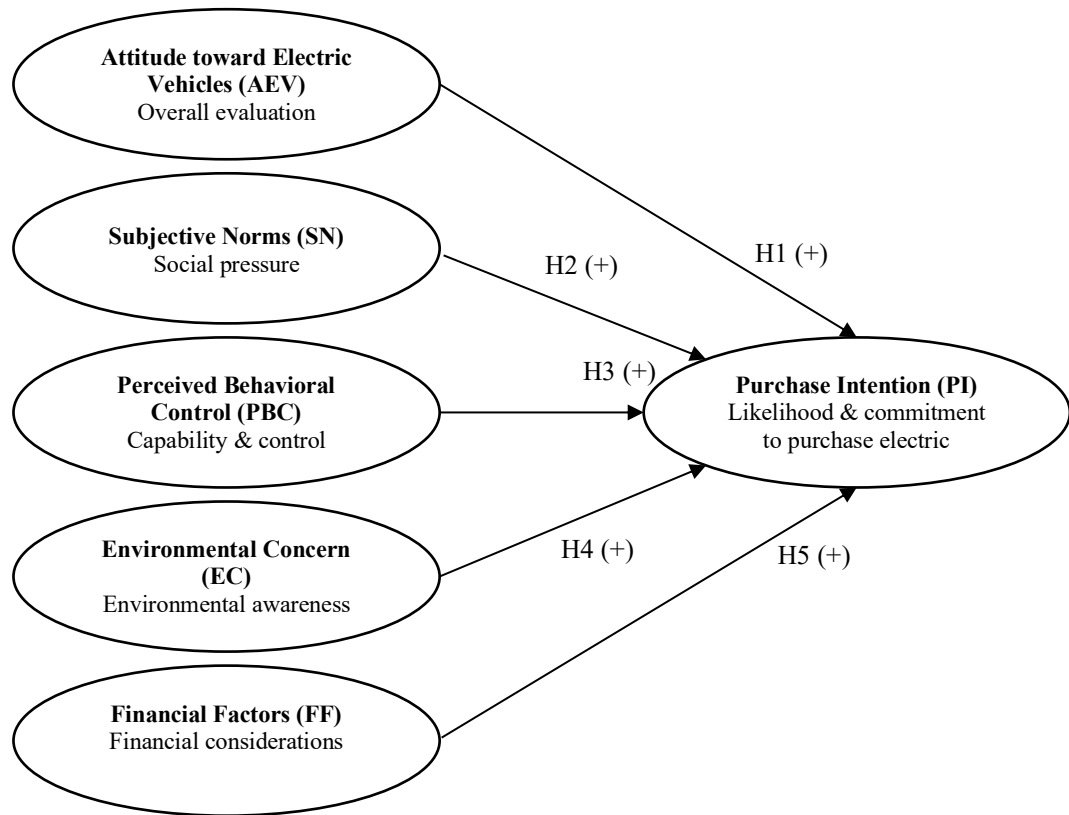
Financial factors capture how consumers assess the economic side of EV ownership, including purchase price, total cost of ownership, and government incentives. Economic evaluation is a major element of consumer decision-making, particularly in developing markets where price has a strong bearing on technology adoption.

The empirical record consistently underlines the importance of economic factors in EV adoption. Falisa and Tricahyono (2025) found that price value makes a significant contribution to EV purchase intention in Indonesia. He and Zhou (2022) likewise showed that economic considerations significantly influence EV purchase intention across consumer income groups. Zhang et al. (2022) reported that government subsidies and pricing risks significantly shape EV adoption decisions in China. Further research in emerging markets confirms that government incentives and perceived cost savings have a positive effect on EV adoption intention.

These results suggest that consumers who see electric vehicles as economically advantageous, affordable, and backed by supportive government policy tend to form stronger purchase intentions. The hypothesis can therefore be stated as follows:

H5: Financial factors have a positive and significant effect on electric vehicle purchase intention.

2.3 Conceptual Framework



The Theory of Planned Behavior offers a comprehensive framework for explaining how consumers decide to adopt new technologies, electric vehicles included. In this study, purchase intention toward electric vehicles is modeled as a function of five determinants: attitude toward EVs, subjective norms, perceived behavioral control, environmental concern, and financial factors. Between them, these capture the psychological, social, control-related, environmental, and financial dimensions that determine whether someone actually intends to adopt an EV.

Building on this framework, the relationships between the five variables and purchase intention are expressed in the following hypotheses:

H1: Attitude toward electric vehicles has a positive and significant effect on purchase intention.

H2: Subjective norms have a positive and significant effect on purchase intention.

H3: Perceived behavioral control has a positive and significant effect on purchase intention.

H4: Environmental concern has a positive and significant effect on purchase intention.

H5: Financial factors have a positive and significant effect on purchase intention.

CHAPTER 3

METHODOLOGY

3.1 Types of Research

This study follows a quantitative approach organized around an explanatory research design. Explanatory research seeks to clarify how variables relate to one another and to test hypotheses derived from an established theoretical framework. Here, the focus is on how attitude toward electric vehicles, subjective norms, perceived behavioral control, environmental concern, and financial factors shape purchase intention toward EVs among potential consumers in DKI Jakarta.

Data was collected by survey, with questionnaires distributed to respondents who satisfied the study's criteria. A quantitative method was adopted so that numerical data could be gathered and the relationships between variables tested statistically. The design is cross-sectional, meaning all data was collected at a single point in time to capture consumers' perceptions of, and intentions toward, electric vehicles.

The research model builds on an extended form of the Theory of Planned Behavior (TPB), which explains behavioral intention through individual attitude, social influence, and perceived behavioral control. Drawing on earlier work in EV adoption, the study widens the model by adding environmental concern and financial factors as additional predictors (Ajzen, 1991; Venkatesh et al., 2003; Sharma & Shalender, 2020; Refor et al., 2023; Falisa & Tricahyono, 2025; Leksana et al., 2025).

3.2 Research Location

The subjects of this study were potential electric vehicle consumers living in DKI Jakarta.

3.3 Population and Sample

The population for this research comprises people living in DKI Jakarta who are aware of and interested in electric vehicles, whether as current EV owners or as prospective buyers. This group is relevant because it consists of consumers who are

directly exposed to EV policies, infrastructure availability, and market developments in Jakarta.

Sampling was carried out through non-probability purposive sampling, with respondents chosen against criteria aligned with the research objectives. To qualify, a respondent had to currently own or plan to buy an electric vehicle, live in DKI Jakarta during the data collection period, and have sufficient knowledge of or exposure to EV products. This approach helps ensure that the data comes from respondents who are in a position to offer meaningful insight into EV purchase intention.

The number of respondents was set according to the minimum sample requirement for Partial Least Squares Structural Equation Modeling (PLS-SEM). Hair et al. (2019) recommend a minimum sample of at least ten times the number of indicators in the research model. With 28 measurement indicators in this study, the minimum sample size works out to 140 respondents.

3.4 Data Sources and Types

The study relies on both primary and secondary data. Primary data is gathered firsthand by the researcher from original sources; here it came from questionnaires completed by residents of DKI Jakarta who met the research criteria, with questions designed to capture respondents' perceptions of electric vehicles and their intentions to buy one.

Secondary data, by contrast, is information that others have already collected and published. In this study it serves to support the background and reinforce the theoretical foundation, and it is drawn from academic journals, research reports, government publications, and other credible sources relating to EV development in Indonesia (Kumar, 2018).

3.5 Data Collection Method

The questionnaire was distributed online through WhatsApp, Google Forms, and the social media platforms most widely used by residents of DKI Jakarta. Online distribution made the collection process faster and helped the researcher reach respondents who matched the study's criteria.

The questionnaire has two sections. The first collects profile information, covering demographic characteristics and how familiar respondents are with electric vehicles. The second measures the research variables using indicators adapted from earlier studies and adjusted to fit the EV adoption context.

Before distribution, a pilot test was run to confirm that the questions were easy for respondents to understand. Participation was entirely voluntary, and respondents were assured that their answers would be kept confidential and used only for academic research. After collection, the data was organized and prepared for statistical analysis.

3.6 Variables and Indicators

The variables consist of independent variables and a dependent variable, each operationalized through a set of measurement indicators. All were adapted from earlier empirical research on electric vehicle adoption and the Theory of Planned Behavior. They are treated as latent constructs and measured on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). This scale is widely used in behavioral research because it lets respondents express their level of agreement in a structured way while still generating enough variance for sound statistical analysis. The variables examined are Attitude toward Electric Vehicles (AEV), Subjective Norms (SN), Perceived Behavioral Control (PBC), Environmental Concern (EC), Financial Factors (FF), and Purchase Intention (PI).

Attitude toward Electric Vehicles (AEV) refers to a respondent's overall evaluation, favorable or unfavorable, of purchasing an electric vehicle. It includes both a cognitive dimension, meaning how respondents judge the benefits of EVs, and an affective dimension, meaning how they feel about owning one. Subjective Norms (SN) capture the social pressure or expectations respondents perceive from family, peers, and society regarding EV adoption. The construct covers injunctive norms, meaning what respondents believe others expect of them, and descriptive norms, meaning how they perceive others actually behaving.

Perceived Behavioral Control (PBC) measures how capable respondents feel of buying and using an electric vehicle. It takes in internal factors, such as

knowledge and financial readiness, together with external ones, such as the availability of infrastructure.

Environmental Concern (EC) reflects how conscious respondents are of environmental sustainability and pollution issues, and how much responsibility they feel toward them. The variable carries particular weight in Jakarta, where poor air quality is a persistent problem.

Financial Factors (FF) describe how respondents perceive the financial side of EV adoption, including affordability, cost efficiency, incentives, and expected economic benefits. The variable also reflects how aware respondents are of government incentive policies connected to EV development.

Purchase Intention (PI) is the behavioral outcome, indicating how likely and willing respondents are to buy an electric vehicle. It covers the strength of that intention, any concrete purchase plans, and behavioral commitment.

All measurement indicators were adapted from established instruments used in earlier research on EV adoption, consumer behavior, and TPB-based models, with small adjustments to keep the wording clear and relevant for respondents in Jakarta. The full operationalization of the variables appears in Table 3.1.

Table 3. 1 Operational Variable Definitions and Measurement Framework

Construct	Operational Definition	Items	Measurement Items & Key Sources
Attitude toward EVs (AEV)	Overall evaluative response to EV adoption including benefits assessment, emotional reactions, and ownership attractiveness	6	AEV1. I have a favorable attitude toward electric vehicles AEV2. Electric vehicles are a good idea for urban transportation in Jakarta AEV3. I find electric vehicles appealing AEV4. Owning an electric vehicle would be beneficial for me AEV5. Electric vehicles represent the future of transportation AEV6. I believe electric vehicles are superior to conventional cars <i>Sources: Sharma & Shalender (2020); Low et al. (2025)</i>
Subjective Norms (SN)	Perceived social pressure and expectations from family, friends,	4	SN1. Most people whose opinions I value would approve of my EV purchase

Construct	Operational Definition	Items	Measurement Items & Key Sources
	and colleagues regarding EV adoption decisions		SN2. People who are important to me expect me to consider buying an electric vehicle SN3. I feel social pressure to consider environmentally friendly transportation SN4. My social circle views electric vehicle ownership positively <i>Sources: Refor et al. (2023); Javid et al. (2022)</i>
Perceived Behavioral Control (PBC)	Perceived ease or difficulty of purchasing and using electric vehicles, including resource availability and self-efficacy	5	PBC1. I have the financial resources to purchase an electric vehicle PBC2. I have the knowledge needed to make an informed EV purchase decision PBC3. I have access to charging infrastructure in Jakarta PBC4. Purchasing an electric vehicle is entirely within my control PBC5. I am confident in my ability to operate and maintain an electric vehicle <i>Sources: Sharma & Shalender (2020); Gayathiri & Ahamed (2025)</i>
Environmental Concern (EC)	Awareness of environmental issues, concern about air quality and climate change, and sense of personal environmental responsibility	5	EC1. I am concerned about air pollution in Jakarta EC2. Climate change is a serious problem that requires immediate action EC3. I feel responsible for reducing my environmental impact through transportation choices EC4. Electric vehicles can help improve air quality in Jakarta EC5. Environmental protection should be prioritized in vehicle purchase decisions <i>Sources: Wang et al. (2016); Leksana et al. (2025)</i>
Financial factors (FF)	Perceptions of financial aspects including affordability, total cost of ownership, and government incentives or policy support	4	EF1. The recent VAT reduction makes electric vehicles more affordable EF2. Electric vehicles offer better long-term cost savings than conventional cars EF3. Government incentives make electric vehicles financially attractive EF4. The total cost of owning an EV is reasonable compared to conventional vehicles

Construct	Operational Definition	Items	Measurement Items & Key Sources
			<i>Sources: Falisa & Tricahyono (2025); He & Zhou (2022)</i>
Purchase Intention (PI)	Likelihood and commitment to purchasing electric vehicles within specified timeframes, including concrete planning	4	PI1. I intend to purchase an electric vehicle in the next 2 years PI2. I plan to consider electric vehicles as my next vehicle purchase PI3. The likelihood of purchasing an EV is high for me PI4. I am determined to make my next vehicle purchase an electric one <i>Sources: Low et al. (2025); Refor et al. (2023)</i>
Total Items:		28	

Note: All measurement items utilize seven-point Likert scales (1 = strongly disagree to 7 = strongly agree).

3.7 Data Analysis Techniques

The data was analyzed to examine the relationships among the research variables and to test the proposed hypotheses. This was done in SmartPLS, which implements Partial Least Squares Structural Equation Modeling (PLS-SEM). The technique is well suited to complex relationships between latent constructs and is widely used in behavioral and consumer research (Hair et al., 2019).

The analysis moved through several stages: instrument testing, classical assumption testing, descriptive statistics, PLS-SEM analysis, and hypothesis testing. Each stage served to confirm that the data met the necessary statistical requirements and was suitable for the structural analysis that followed.

3.7.1 Instrument Testing

Instrument testing was carried out to make sure the questionnaire measures the intended variables both accurately and consistently. It comprises two parts: validity testing and reliability testing.

3.7.1.1 Validity Test

Validity testing establishes whether the questionnaire items genuinely capture the variables under study. An instrument is considered valid when its items faithfully represent the construct they are meant to measure.

Two forms of validity are assessed: convergent and discriminant. Convergent validity is judged by the Average Variance Extracted (AVE), where a value above 0.50 shows that the indicators explain an adequate share of their underlying construct (Fornell & Larcker, 1981). Discriminant validity is checked in two ways. The Fornell-Larcker criterion requires that the square root of each construct's AVE be larger than its correlation with every other construct, and the Heterotrait-Monotrait ratio (HTMT) must remain below 0.85. When both conditions are met, each construct can be regarded as empirically distinct from the others (Henseler et al., 2015).

3.7.1.2 Reliability Test

Reliability testing gauges the consistency and stability of the measurement instrument. Reliability here is evaluated through Cronbach's Alpha and Composite Reliability (CR), both of which must exceed the recommended threshold of 0.70 to show that the items consistently measure the same construct (Hair et al., 2019). Composite reliability is particularly important in PLS-SEM because it takes into account how much each indicator actually contributes to its construct.

3.7.2 Classical Assumption Test

The classical assumption test checks whether the data satisfies the statistical requirements needed before structural analysis can proceed. It helps ensure that the regression relationships between variables can be interpreted accurately.

3.7.2.1 Multicollinearity Test

Multicollinearity testing determines whether the independent variables in the model are excessively correlated with one another. High multicollinearity can distort path coefficient estimates and weaken the reliability of the model. This study uses the Variance Inflation Factor (VIF) to make the assessment. A VIF below 10 indicates that multicollinearity is not a concern and that the independent variables can be used together in the structural model (Hair et al., 2019).

3.7.3 Descriptive Statistics

Descriptive statistical analysis provides a general picture of the respondents and of how they responded to the research variables. It summarizes demographic details such as age, occupation, and familiarity with electric vehicles, and presents the distribution of responses for each measurement item, including mean values and overall response tendencies. This stage gives an early sense of respondents' perceptions before the structural analysis begins.

3.7.4 PLS-SEM Analysis

The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which evaluates the measurement model and the structural model at the same time. The method suits this study because it supports both predictive and explanatory analysis, which is especially valuable in research built around behavioral constructs and complex relationships among latent variables (Sarstedt & Cheah, 2019).

PLS-SEM combines elements of factor analysis and multiple regression, allowing the researcher to examine how observed indicators relate to latent constructs and how those constructs are causally linked within the model. Where covariance-based SEM emphasizes overall model fit, PLS-SEM prioritizes predictive capability, which gives it greater flexibility in social science research (Hair et al., 2019).

The analysis proceeds in two stages. First, the measurement model (outer model) is evaluated to confirm that the indicators for each construct are reliable and valid. Second, the structural model (inner model) is tested to determine the strength, direction, and significance of the relationships among the latent variables.

Several methodological considerations common in behavioral research also support the choice of PLS-SEM. The technique handles relatively small samples, non-normal data distributions, and models with multiple reflective constructs. It can accommodate complex research models without imposing strict statistical assumptions, and it lends itself well to predictive modeling (Latan & Ghazali, 2012).

The use of PLS-SEM therefore fits the objective of this study, which is to examine how attitude toward electric vehicles, subjective norms, perceived

behavioral control, environmental concern, and financial factors relate to purchase intention among potential EV buyers in DKI Jakarta.

3.7.5 SEM-PLS Evaluation Criteria

The SEM-PLS model is evaluated at two levels, the measurement model and the structural model, against widely accepted statistical criteria. This step is essential because it confirms that the research model is statistically reliable, valid, and capable of explaining the relationships among the variables.

The first stage concerns the measurement model and aims to confirm that the indicators accurately reflect the constructs they are meant to measure. Several criteria apply. Indicator reliability is assessed through outer loadings, with values above 0.70 considered reliable (Hair et al., 2019). Internal consistency reliability is judged by Cronbach's Alpha and Composite Reliability, where values over 0.70 indicate acceptable reliability (Hair et al., 2019). Convergent validity is examined via the Average Variance Extracted (AVE), where a value above 0.50 shows that a construct explains more than half the variance in its indicators (Fornell & Larcker, 1981). Discriminant validity is checked by comparing the square root of each construct's AVE with its correlations with other constructs, and through the Heterotrait-Monotrait ratio (HTMT), where values below 0.85 indicate adequate discriminant validity (Henseler et al., 2015).

The second stage turns to the structural model, which examines how the latent variables relate to one another and how well the model predicts outcomes. Path coefficients show the strength and direction of each relationship, while the coefficient of determination (R^2) indicates the proportion of variance in the dependent variable explained by the independent variables. R^2 values of 0.25, 0.50, and 0.75 correspond to weak, moderate, and substantial explanatory power (Chin, 1998). Effect size (f^2) measures the contribution of each independent variable to the dependent variable, with 0.02, 0.15, and 0.35 marking small, medium, and large effects (Cohen, 1988). Predictive relevance (Q^2) assesses the model's predictive capability, with values above zero indicating that the model has predictive relevance (Hair et al., 2019). The full set of evaluation criteria applied in this study is summarized in Table 3.2.

Table 3.2 Operational Variable Definitions and Measurement Framework

Criteria	Explanation
Evaluation of Measurement Model	
Internal Consistency	Cronbach's Alpha and Composite Reliability >0.7
Convergent Validity	Average Variance Extracted (AVE) >0.5
Discriminant Validity	Intended construct loading value > loading value of other constructs
Evaluation of Structural Model	
Structural Path Coefficient	Close to +1 reflects strong relationship and statistically significant
Coefficient or Determination R²	R ² result of 0.75, or 0.50, or 0.25 for endogenous latent variables indicates the model is "good", "moderate", and "weak" respectively.
Effect Size f²	f ² values of 0.02, or 0.15, 0.35 indicates the predictors of latent variables have a weak, medium, or strong influence, respectively.

Table 3. 3

Source : Hair et.al (2014), Ghozali (2018)

3.7.6 Hypothesis Testing

Hypothesis testing determines whether the relationships proposed between the variables hold up statistically. It relies on the bootstrapping procedure in SmartPLS, which generates t-statistics and p-values for every structural path in the model.

Hypotheses are accepted or rejected on the basis of the following criteria:

- A hypothesis is accepted when the t-statistic exceeds the critical value ($t > 1.96$ for a two-tailed test, or $t > 1.65$ for a one-tailed test, at $\alpha = 0.05$).
- A hypothesis is also accepted when the p-value falls below 0.05, indicating a statistically significant relationship between the constructs.

- The sign of the path coefficient shows whether the relationship between variables is positive or negative, confirming the direction proposed in the research model.
- The size of the path coefficient reflects the strength of the relationship, with larger absolute values indicating a stronger influence.

Through this procedure, the study assesses whether attitude toward electric vehicles, subjective norms, perceived behavioral control, environmental concern, and financial factors have a significant effect on EV purchase intention among consumers in DKI Jakarta. The results of the hypothesis testing are presented and discussed in Chapter 4 (Results and Analysis).

CHAPTER IV

DATA ANALYSIS

4.1 Research Description

This chapter presents the results of the data analysis conducted to examine what shapes consumers' intention to buy electric vehicles (EVs) in DKI Jakarta. The study took a quantitative approach, applying Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. The population consisted of DKI Jakarta residents who met the research criteria and could be regarded as potential EV buyers. In all, 197 respondents took part by completing an online questionnaire distributed through Google Forms. They were selected by purposive sampling against set criteria: being at least 18 years old, having some familiarity with electric vehicles, and being a prospective EV buyer. The responses were analyzed in SmartPLS 4 to evaluate both the measurement model (outer model) and the structural model (inner model). The analysis covered descriptive statistics, validity and reliability assessment, hypothesis testing, the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2).

4.1.1 Respondent Overview

a. Respondent Characteristics Based on Gender

Respondent characteristics by gender are summarized in Table 4.1.

Table 4.1
Respondent Characteristics Based on Gender

Gender	Frequency	Percentage
Male	61	31%
Female	136	69%
Total	197	100%

Source: Primary Data Processed by the Researcher (2026)

Table 4.1 shows that, of the 197 respondents who took part, a clear majority were women, although both genders are represented. Having both groups in the sample allows the study to pick up on where perceptions of EV purchase intention differ between men and women and where they align. As noted earlier, data was

collected through an online questionnaire sent to DKI Jakarta residents over the course of the research period.

b. Respondent Characteristics Based on Age

Respondent characteristics by age are summarized in Table 4.2.

Table 4.2

Respondent Characteristics Based on Age

Age	Frequency	Percentage
Below 25 years	11	5,6%
26–35 Years	144	73.1%
36–45 Years	27	13.7%
Above 45 Years	15	7,6%
Total	197	100%

Source: Primary Data Processed by the Researcher (2026)

Table 4.2 shows that respondents came from a range of age groups, with most falling into the productive working-age bracket. People in this group tend to be more open to technological innovation and sustainable transportation, so the distribution offers a useful view of how purchase intentions toward electric vehicles play out across generations.

c. Respondent Characteristics Based on Educational Level

Respondent characteristics by educational level are summarized in Table 4.3.

Table 4.3

Respondent Characteristics Based on Educational Level

Education	Frequency	Percentage
High School / Equivalent	11	5,6%
Diploma (D3)	7	3,6%
Bachelor's Degree (S1)	111	56,3%
Master's Degree (S2)	62	31%
Doctoral Degree (S3)	6	3%
Total	197	100%

Source: Primary Data Processed by the Researcher (2026)

Table 4.3 sets out the educational background of the respondents. Their qualifications range from high school graduates to holders of postgraduate degrees. This variety improves how well the sample reflects the wider population and brings a broader mix of perspectives to bear on EV adoption and purchase intention.

d. Respondent Characteristics Based on Monthly Income

Respondent characteristics by monthly income are summarized in Table 4.4.

Table 4.4
Respondent Characteristics Based on Monthly Income

Occupation	Frequency	Percentage
Below 10 millions	55	27,9%
10 – 20 millions	81	41,1%
20 – 30 millions	50	25,4%
30 – 50 millions	6	3%
Above 50 millions	5	2,5%
Total	197	100%

4.1.2. Instrument Validity and Reliability

To confirm the accuracy and consistency of the data collected, the study includes validity and reliability tests, as outlined in Chapter 3. SmartPLS was used to compute and assess the data. Several measures were applied to this end, including construct validity, discriminant validity, and convergent validity.

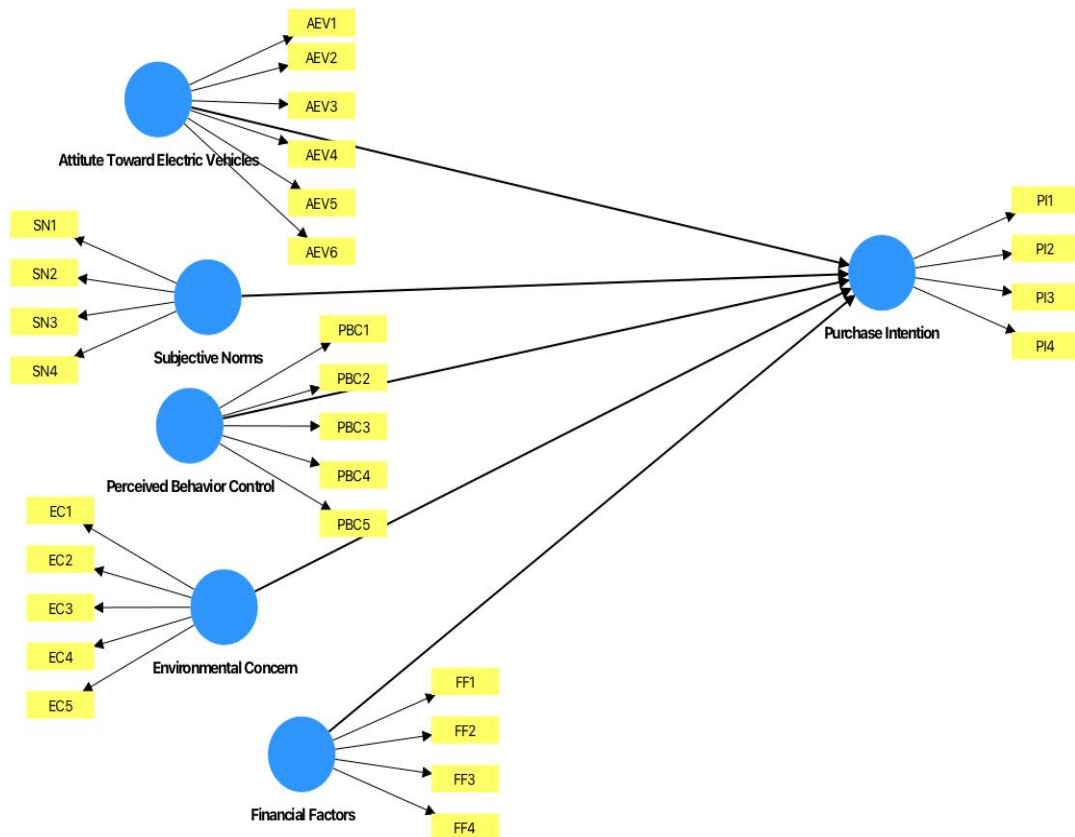


Figure 4.1 The Path Model – Initial Version (PLS Algorithm Result)

The path model was developed and proposed on the basis of the underlying model shown in Figure 4.1, and was then tested for validity and reliability.

4.1.3 Indicator Loadings

Following Hair (2018), the first step in evaluating a reflective measurement model is to inspect the indicator loadings. All indicators in the model show acceptable loadings (>0.708).

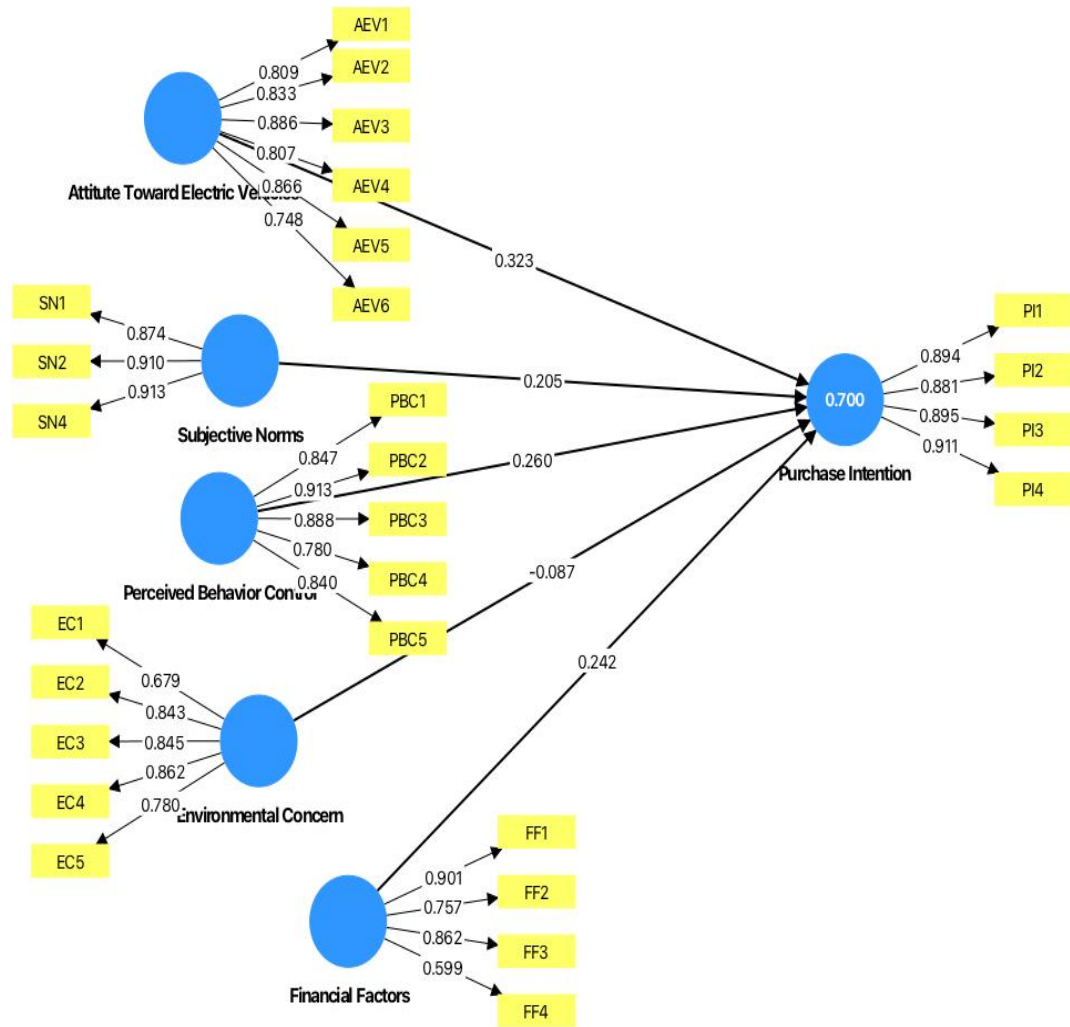


Figure 4.2 Initial Validiy Test

Outer loadings indicate how well each observed indicator represents the latent construct it belongs to. Hair et al. (2019) recommend loadings of at least 0.708 as evidence that an indicator contributes meaningfully to its construct. Indicators that fall below that level can still be retained, provided the construct's composite reliability (CR) and average variance extracted (AVE) remain acceptable and there is sound theoretical justification for keeping them. Indicators with loadings below 0.4, on the other hand, are generally removed because they add very little.

Attitude Towards Electric Vehicles

Indicators:

Table 4.5

Attitude Towards Electric Vehicles Outer Loadings

Variable	Score
Attitude Towards Electric Vehicles 1	0.809
Attitude Towards Electric Vehicles 2	0.833
Attitude Towards Electric Vehicles 3	0.886
Attitude Towards Electric Vehicles 4	0.807
Attitude Towards Electric Vehicles 5	0.866
Attitude Towards Electric Vehicles 6	0.748

Analysis: Every indicator shows an outer loading above 0.708, indicating a strong contribution to the Attitude Towards Electric Vehicles construct. These values confirm that the observed variables (AEV1 – AEV6) measure Attitude Towards Electric Vehicles reliably and validly. No indicator needs to be removed, and the results are consistent with theoretical expectations.

Subjective Norms

Indicators:

Table 4.6

Subjective Norms Outer Loadings

Variable	Score
Subjective Norms 1	0.874
Subjective Norms 2	0.910
Subjective Norms 4	0.913

Analysis: All outer loadings sit well above 0.708, showing that the indicators explain the Subjective Norms construct very effectively. The results point to high reliability and strong construct validity.

Perceived Behaviour Control

Indicators:

Table 4.7

Perceived Behaviour Control Outer Loadings

Variable	Score
Perceived Behaviour Control 1	0.847
Perceived Behaviour Control 2	0.913
Perceived Behaviour Control 3	0.888
Perceived Behaviour Control 4	0.780
Perceived Behaviour Control 5	0.840

Analysis: Outer loadings for every indicator exceed 0.708, confirming a strong contribution to the Perceived Behaviour Control construct. These high values support the measurement model for Perceived Behavior Control and confirm that it is adequate and robust.

Environmental Concern indicators:

Table 4.8

Environmental Concern Outer Loadings

Variable	Score
Environmental Concern 1	0.679

Environmental Concern 2	0.843
Environmental Concern 3	0.845
Environmental Concern 4	0.862
Environmental Concern 5	0.780

Analysis:

Most of the outer loadings exceed 0.708, indicating a strong contribution to the Environmental Concern construct. EC1 (0.679), however, falls just short of the ideal threshold of 0.708. It is nonetheless retained for the following reasons:

- The loading (0.679) is above the minimum threshold of 0.4
- The overall composite reliability (CR = 0.901) and AVE (0.647) remain satisfactory
- There is theoretical justification for keeping it

EC1 is therefore kept despite its slightly lower loading, since the construct's overall validity remains robust.

Financial Factors

Indicators:

Table 4.9
Financial Factors Outer Loadings

Variable	Score
Financial Factors 1	0.901
Financial Factors 2	0.757
Financial Factors 3	0.862
Financial Factors 4	0.599

Analysis:

Most indicators exceed 0.708, demonstrating a strong contribution. FF4 (0.599), however, is noticeably below the 0.708 threshold. It is nonetheless retained for the following reasons:

- The loading (0.599) is above the removal threshold of 0.4
- The overall composite reliability (CR = 0.865) and AVE (0.621) remain acceptable
- There is theoretical justification for keeping it

Note: FF4 deserves consideration for refinement or replacement with a more strongly correlated indicator in future work, since its contribution is comparatively weaker than that of the other items in this construct.

Purchase Intentions**Indicators:**

Table 4.10
Purchase Intentions Outer Loadings

Variable	Score
Purchase Intentions 1	0.894
Purchase Intentions 2	0.881
Purchase Intentions 3	0.895
Purchase Intentions 4	0.911

Analysis: Outer loadings for every indicator exceed 0.708, confirming a strong contribution to the Purchase Intentions construct. These high values support the measurement model for Purchase Intentions and confirm that it is adequate and robust.

4.1.4. Internal Consistency Reliability

Internal consistency reliability is the next key element of the reflective measurement assessment (Hair et al., 2019). As shown in Table 4.5, this involves both composite reliability and Cronbach's alpha. Composite reliability for all constructs falls between 0.80 and 0.90, a range described as "satisfactory to good" (Hair et al., 2019), meaning reliability is good though not exceptional. The Cronbach's Alpha values point to the same conclusion, with every construct again falling between 0.80 and 0.90.

Table 4.11
Reliability Test Result

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracte d (AVE)
Attitude Toward Electric Vehicles	0,906	0,908	0,928	0,682
Environmental Concern	0,863	0,883	0,901	0,647
Financial Factors	0,792	0,823	0,865	0,621
Perceived Behavior Control	0,907	0,913	0,931	0,731
Purchase Intention	0,917	0,919	0,942	0,801
Subjective Norms	0,881	0,882	0,927	0,808

4.1.5 Convergent Validity

The convergent validity test, a required part of the reflective measurement evaluation, was run in SmartPLS. It relies on the Average Variance Extracted (AVE). According to Bagozzi and Yi (1989), a construct shows strong convergent validity when its AVE is ≥ 0.5 .

Table 4.12

Variable	Average Variance Extracted (AVE)	Results
Attitude Toward Electric Vehicles	0.682	Good and Acceptable Validity
Environmental Concern	0.647	Good and Acceptable Validity
Financial Factors	0.621	Good and Acceptable Validity
Perceived Behavior Control	0.731	Good and Acceptable Validity
Purchase Intention	0.801	Good and Acceptable Validity
Subjective Norms	0.808	Good and Acceptable Validity

Table 4.12 presents the results of the convergent validity test. All AVE values are comfortably ≥ 0.50 , which means each construct explains at least 50% of the variance in its indicators.

4.1.6 Discriminant Validity

Discriminant validity was evaluated using the Fornell-Larcker criterion. The results of that analysis, obtained through SmartPLS, are shown in Table 4.5, which sets out the correlations between latent variables alongside the square root of the AVE values.

Table 4.13
Fornell-Lacker Criterion Analysis

	AEV	EC	FF	PBC	PI	SN
AEV	0,826					
EC	0,734	0,804				
FF	0,707	0,722	0,788			
PBC	0,803	0,679	0,589	0,855		
PI	0,791	0,643	0,657	0,763	0,895	
SN	0,747	0,695	0,472	0,785	0,703	0,899

On this basis, the questionnaire can be said to have strong discriminant validity, since the square root of AVE for each latent variable is greater than its correlation with the other latent variables. The square-root values for AEV (0.826), EC (0.804), FF (0.788), PBC (0.855), PI (0.895), and SN (0.899) all exceed their respective correlations with other constructs, which shows that each construct is more closely related to its own indicators than to those of any other construct. The cross-loading test in Table 4.8 supports the same conclusion.

Table 4.14
Cross-Loading Test

	Attitude Toward Electric Vehicles	Environmental Concern	Financial Factors	Perceived Behavior Control	Purchase Intention	Subjective Norms
AEV1	0,809	0,550	0,545	0,576	0,642	0,483
AEV2	0,833	0,629	0,537	0,686	0,608	0,617
AEV3	0,886	0,648	0,650	0,675	0,715	0,649
AEV4	0,807	0,609	0,474	0,733	0,675	0,748
AEV5	0,866	0,687	0,675	0,687	0,629	0,611
AEV6	0,748	0,513	0,617	0,620	0,640	0,581
EC1	0,488	0,679	0,601	0,359	0,391	0,268
EC2	0,544	0,843	0,493	0,563	0,417	0,612
EC3	0,549	0,845	0,539	0,519	0,512	0,556
EC4	0,736	0,862	0,720	0,639	0,638	0,615
EC5	0,582	0,780	0,524	0,597	0,559	0,676
FF1	0,592	0,638	0,901	0,446	0,505	0,343
FF2	0,688	0,740	0,757	0,621	0,597	0,642
FF3	0,554	0,558	0,862	0,515	0,575	0,367

FF4	0,310	0,209	0,599	0,147	0,328	-0,042
PBC1	0,663	0,538	0,516	0,847	0,643	0,597
PBC2	0,760	0,609	0,527	0,913	0,727	0,716
PBC3	0,686	0,600	0,464	0,888	0,657	0,723
PBC4	0,574	0,483	0,504	0,780	0,578	0,526
PBC5	0,738	0,667	0,509	0,840	0,646	0,780
PI1	0,669	0,487	0,593	0,648	0,894	0,538
PI2	0,728	0,681	0,544	0,775	0,881	0,813
PI3	0,712	0,593	0,610	0,661	0,895	0,605
PI4	0,721	0,527	0,608	0,636	0,911	0,538
SN1	0,727	0,610	0,482	0,709	0,628	0,874
SN2	0,618	0,571	0,355	0,676	0,607	0,910
SN4	0,668	0,689	0,433	0,730	0,659	0,913

4.1.7 Collinearity Assessment

To confirm that each indicator contributes something distinct and meaningful to the Average Variance Extracted (AVE), and to rule out redundancy among them, a collinearity assessment was carried out. This check makes sure the indicators capture different information rather than overlapping, so that each one adds non-redundant value to the measurement of its latent construct (Sarstedt et al., 2017). Collinearity is evaluated using the Variance Inflation Factor (VIF), with values compared against established thresholds. A VIF between 3 and 5 signals moderate collinearity that is generally not a problem, while a VIF below 3 indicates no collinearity at all (Hair et al., 2022; Sarstedt et al., 2017).

Table 4.15 Collinearity Results

	VIF
AEV1	2,991
AEV2	2,881
AEV3	3,279
AEV4	2,482
AEV5	2,922
AEV6	1,848
EC1	2,324
EC2	2,585
EC3	2,490
EC4	2,387
EC5	2,607

FF1	2,902
FF2	1,732
FF3	2,102
FF4	1,662
PBC1	2,453
PBC2	3,870
PBC3	3,526
PBC4	1,908
PBC5	2,391
PI1	3,169
PI2	2,516
PI3	2,921
PI4	3,551
SN1	2,080
SN2	2,864
SN4	2,792

Source: Processed by SmartPLS 4 (2026)

As Table 4.15 shows, all indicators apart from AEV3, PBC2, PBC3, PI1, and PI4 have Variance Inflation Factor (VIF) values below 3, pointing to minimal collinearity and suggesting that these indicators contribute distinctly to their latent constructs. The VIF values for AEV3, PBC2, PBC3, PI1, and PI4 are above 3 but still within a justifiable range, indicating moderate collinearity. Although this suggests some overlap among these indicators, the degree of collinearity is not severe and is generally acceptable.

4.2 Structural Model Evaluation and Hypothesis Test

Structural model evaluation in PLS-SEM involves analyzing the strength, direction, and significance of the relationships between latent variables. This assessment is important for establishing whether the hypothesized relationships hold within the data and for understanding the predictive power of the model.

The main elements of structural model evaluation are the path coefficients, R-square values, and effect sizes.

The R-Square and path coefficient results from the measurement model are

then used to run hypothesis tests in SmartPLS through bootstrapping.

4.2.1 Path Coefficient

Path coefficients were calculated to examine the strength and direction of the associations between the exogenous and endogenous constructs in the structural model. These coefficients generally range from -1 to +1: values close to either extreme indicate stronger and more meaningful relationships, whereas values near zero indicate weaker associations and less explanatory power (Hair et al., 2022; Sarstedt et al., 2017).

Table 4.16
Path Coefficient Results

Hypothesis	Path coefficients
Attitude Toward Electric Vehicles -> Purchase Intention	0,323
Environmental Concern -> Purchase Intention	-0,087
Financial Factors -> Purchase Intention	0,242
Perceived Behavior Control -> Purchase Intention	0,260
Subjective Norms -> Purchase Intention	0,205

Table 4.16 reports the path coefficients, which describe the strength and direction of the relationships between the independent variables and Purchase Intention toward Electric Vehicles. Most of these relationships are positive, meaning that higher levels of the variables go hand in hand with stronger purchase intentions. Of the predictors, Attitude Toward Electric Vehicles has the strongest positive effect on Purchase Intention, with a path coefficient of 0.323, indicating that people with a more favorable attitude toward EVs are more likely to intend to buy one. It is followed by Perceived Behavioral Control (0.260) and Financial Factors (0.242), which suggests that consumers who feel more in control of the purchasing process and who view the financial side favorably tend to report stronger purchase intentions.

Subjective Norms also show a positive relationship with Purchase Intention,

with a path coefficient of 0.205, indicating that social influence from family, friends, or significant others contributes positively to consumers' intention to purchase electric vehicles. Environmental Concern, in contrast, has a path coefficient of -0.087, reflecting a weak negative relationship with Purchase Intention. At least within this study, environmental concern on its own is not sufficient to drive consumers' intentions to buy an EV in any meaningful way.

Overall, the results identify Attitude Toward Electric Vehicles as the strongest predictor of Purchase Intention, followed by Perceived Behavioral Control, Financial Factors, and Subjective Norms. Environmental Concern, by comparison, shows only a weak negative effect on Purchase Intention.

4.2.2 Coefficient of Determination (R²)

R-Square (R²) measures how well the model explains the variance in its constructs, which is why it is also described as in-sample predictive power (Rigdon, 2012). The results in Table 4.17 show an R² of 0.7 for Purchase Intention, meaning the independent variables in the model account for 70% of its variance. This represents strong explanatory power and suggests that the chosen predictors capture most of what drives the construct. The remaining 30%, however, points to other influences not included in the model, along with random error, that also play a part in the outcome. According to Hair et al. (2017), values of this size indicate substantial explanatory ability.

Table 4.17
R² Test Result

	R-square	R-square adjusted
Purchase Intention	0,700	0,692

In the structural model presented in Table 4.17, the R² for Purchase Intention is 0.700 and the adjusted R² is 0.692. The model therefore explains 70.0% of the variance in Purchase Intention. The adjusted R², which corrects for the number of predictors, is slightly lower at 69.2% but still reflects strong explanatory power. The small gap between the two values suggests that the predictors make a relatively stable contribution to explaining Purchase Intention and that the model does not appear to suffer from serious overfitting.

In the context of social science research, an R² of 0.700 shows that the model

has substantial explanatory power, sitting close to the substantial threshold suggested in earlier PLS-SEM literature. The independent variables in this study are thus able to explain a considerable share of the variance in consumers' Purchase Intention, while the remaining 30.0% may be attributable to factors outside the model. Following Hair et al. (2017), these values indicate that the structural model has adequate explanatory capability for predicting the dependent variable, Purchase Intention.

4.2.3 The Effect Size (F2)

In PLS-SEM, the F^2 statistic is used to gauge the effect size of each predictor on the dependent variable. It is calculated for every path relationship to determine how much the exogenous variable influences the endogenous variable, making it an essential measure of the relative strength and practical significance of each predictor. F^2 values are conventionally classed as small, medium, or large at thresholds of 0.02, 0.15, and 0.35 respectively. A higher F^2 value indicates a stronger and more substantive effect of the predictor on the endogenous variable. Examining effect sizes carefully allows researchers to better understand the practical implications of their findings and to draw more nuanced conclusions about the strength of the relationships in their models.

Table 4.17
F2 Test Result

	f-square
Attitude Toward Electric Vehicles -> Purchase Intention	0,082
Environmental Concern -> Purchase Intention	0,008
Financial Factors -> Purchase Intention	0,072
Perceived Behavior Control -> Purchase Intention	0,061
Subjective Norms -> Purchase Intention	0,041

Table 4.17 reveals a range of effect sizes across the pathways to Purchase Intention. Attitude Toward Electric Vehicles shows the largest effect size at 0.082, suggesting a small to moderate impact on Purchase Intention. Financial Factors also produce a meaningful effect size of 0.072, reflecting a notable contribution to

purchase intentions. Environmental Concern, by contrast, shows a negligible effect size of 0.008, indicating virtually no impact on Purchase Intention. Both Perceived Behavior Control (0.061) and Subjective Norms (0.041) display relatively weak effect sizes, suggesting limited direct influence on consumers' purchase intentions. These findings highlight the differing importance of the factors in predicting purchase behavior, with some variables showing considerably more practical significance than others in shaping consumers' intention to buy electric vehicles.

4.2.4 Hypothesis Testing

The final step of the analysis is to assess the statistical significance and relevance of the path coefficients for hypothesis testing. The path significance results and the hypothesized constructs are shown in Table 4.10.

Table 4.18
Path coefficients – Direct Effect

Hypothesis	Path coefficients	t-value	p-value	Results
Attitude Toward Electric Vehicles -> Purchase Intention	0,323	2,956	0,002	Supported
Environmental Concern -> Purchase Intention	-0,087	1,035	0,150	Not Supported
Financial Factors -> Purchase Intention	0,242	2,666	0,002	Supported
Perceived Behavior Control -> Purchase Intention	0,260	2,604	0,005	Supported
Subjective Norms -> Purchase Intention	0,205	2,499	0,006	Supported

- H1: Attitude Toward Electric Vehicles → Purchase Intention

The path coefficient of 0.323 indicates a moderate positive relationship between Attitude Toward Electric Vehicles and Purchase Intention. The t-value of 2.956 exceeds the 1.96 threshold, and the p-value of 0.002 is below 0.05.

- H2: Subjective Norms → Purchase Intention

The path coefficient of 0.205 indicates a positive relationship between Subjective Norms and Purchase Intention. The t-value of 2.499 exceeds 1.96, and the p-value of 0.006 is below 0.05.

- H3: Perceived Behavioral Control → Purchase Intention

The path coefficient of 0.260 indicates a moderate positive relationship between Perceived Behavioral Control and Purchase Intention. The t-value of 2.604 is above the 1.96 threshold, and the p-value of 0.005 is below 0.05.

- H4: Environmental Concern → Purchase Intention

The path coefficient of -0.087 indicates a weak negative relationship between Environmental Concern and Purchase Intention. The t-value of 1.035 falls below the 1.96 threshold, so the relationship is not statistically significant.

- H5: Financial Factors → Purchase Intention

The path coefficient of 0.242 indicates a moderate positive relationship between Financial Factors and Purchase Intention. The t-value of 2.666 exceeds 1.96, and the p-value of 0.002 is below 0.05.

This section considers how each construct relates to Purchase Intention (PI), drawing on the path coefficient and significance results. The aim is to see how Attitude Toward Electric Vehicles (AEV), Environmental Concern (EC), Financial Factors (FF), Perceived Behavioural Control (PBC), and Subjective Norms (SN) each influence whether consumers genuinely intend to buy an EV.

Attitude turned out to be the strongest predictor of all, with a path coefficient of 0.323. In practical terms, the more positively someone views EVs, the more likely they are to form a real intention to buy one. Perceived Behavioural Control came next at 0.260, also statistically significant, showing that people's sense of their own capacity, both the resources at hand and the ability to buy and use an EV, plays a meaningful role in shaping their intention.

Financial Factors followed closely at 0.242, underscoring how much affordability, purchase price, running costs, and expected financial returns figure in

people's thinking when they consider going electric. Subjective Norms completed the set of significant predictors with a coefficient of 0.205, positive and significant. Encouragement or pressure from family, friends, peers, and the wider community, in other words, does affect whether people begin to take an EV purchase seriously.

Environmental Concern (EC) is the exception. Its relationship with Purchase Intention was weakly negative, with a path coefficient of -0.087, and not statistically significant given a t-value of 1.035. Environmental concern by itself, then, does not translate into a meaningful intention to buy an EV among the respondents in this study. Even when consumers recognize the environmental advantages of EVs, other considerations, namely personal attitude, perceived ability, financial factors, and social influence, appear to matter far more in the decision.

Taken together, the findings show that Purchase Intention toward electric vehicles is driven first by consumers' attitudes, then by perceived behavioral control, financial considerations, and subjective norms. The comparatively strong role of attitude suggests that fostering positive perceptions of and experiences with EVs may be particularly valuable in encouraging adoption. Beyond that, making EVs more affordable and accessible, building supporting infrastructure, and cultivating wider social acceptance could all help move consumers from general awareness toward a firm intention to buy.

Environmental concern, on the other hand, does not appear strong enough on its own to shift purchase intention in a significant way. This underlines the need to combine environmental messaging with practical, financial, and social benefits when promoting EV adoption.

4.3 Discussion on Findings

This section looks more closely at the study's findings, examining how attitude toward electric vehicles, environmental concern, financial factors, perceived behavioral control, and subjective norms shape purchase intention among prospective EV buyers in DKI Jakarta. The results are read through the lens of the Theory of Planned Behavior (Ajzen, 1991), with attention to what each construct adds to the academic understanding of green consumer behavior in this setting.

4.3.1 Influence of Attitude Toward Electric Vehicles on Purchase Intention

Among all the constructs, attitude toward electric vehicles had the strongest positive relationship with purchase intention ($\beta = 0.323$, $t = 2.956$, $p = 0.002$), making it the leading predictor in the model. In practice, consumers who regard EVs favorably, whether in terms of performance, environmental benefit, or modernity, are considerably more inclined to form an intention to buy one. This fits squarely within the Theory of Planned Behavior (Ajzen, 1991), which treats attitude toward a behavior as a core antecedent of intention, and it suggests that cultivating positive perceptions of EVs remains the single most effective lever for encouraging adoption in this market.

4.3.2 Influence of Environmental Concern on Purchase Intention

Environmental concern, in contrast, showed only a weak negative relationship with purchase intention, and one that was not statistically significant ($\beta = -0.087$, $t = 1.035$). Among the respondents in this study, simply being aware of environmental problems does not by itself reliably produce an intention to buy an EV. The pattern echoes the well-documented "attitude–behavior gap" in green consumer research, where environmental values are clearly present but end up outweighed by more immediate, practical concerns such as cost and convenience. The implication is that environmental messaging on its own is unlikely to move the needle on EV adoption unless it is paired with tangible functional or financial benefits. Purchasing EV in DKI Jakarta is not about environmental concern, is more about attitude, financial factors, and perceive behavioral control.

4.3.3 Influence of Financial Factors on Purchase Intention Financial factors

Financial factors had a significant positive effect on purchase intention ($\beta = 0.242$, $t = 2.666$, $p = 0.002$). Considerations such as purchase price, incentives, charging costs, and long-term savings clearly shape consumers' willingness to buy an EV. The result supports the view that adopting an EV is, to a large extent, a rational economic decision, and it highlights how much affordability and financial incentives, whether subsidies or tax relief, matter in accelerating market uptake.

4.3.4 Influence of Perceived Behavioral Control on Purchase Intention

Perceived behavioral control likewise had a significant positive effect on purchase intention ($\beta = 0.260$, $t = 2.604$, $p = 0.005$). Consumers who believe they have the resources, knowledge, and access needed to run an EV, from reachable charging facilities to straightforward ownership, are more likely to intend to buy one. This mirrors Ajzen's (1991) treatment of perceived behavioral control as a proxy for actual control over a behavior, and it underscores how much infrastructure development and consumer education can do to strengthen EV purchase intention.

4.3.5 Influence of Subjective Norms on Purchase Intention

Subjective norms showed a significant positive relationship with purchase intention ($\beta = 0.205$, $t = 2.499$, $p = 0.006$). Social influence from family, peers, and the surrounding community therefore plays a meaningful part in shaping whether consumers intend to buy an EV. Given Indonesia's relatively collectivist social context, the approval or example of close social groups appears to carry real weight in this decision, which in turn suggests that word-of-mouth and visible early adoption within social circles can do much to support wider market diffusion.

4.3.6 Implications for the Electric Vehicle Market in DKI Jakarta

The model accounted for 70% of the variance in purchase intention ($R^2 = 0.700$), a sign of strong explanatory power. Taken together, the findings suggest that attitude, financial factors, perceived behavioral control, and subjective norms all play significant and complementary roles in shaping EV purchase intention, while environmental concern alone is not enough to drive adoption. For manufacturers, dealers, and policymakers, this implies that strategies should focus on (1) building positive attitudes through test drives, transparent performance information, and visible endorsements; (2) reducing financial barriers through incentives and flexible financing; (3) expanding charging infrastructure and simplifying ownership to strengthen perceived behavioral control; and (4) drawing on social proof and community-based campaigns to activate subjective norms. Environmental appeals should be combined with these practical and social levers rather than used as a standalone selling point.

CHAPTER V

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter draws together the conclusions arising from the data analysis in Chapter IV and considers how far the research objectives have been achieved. It then sets out the study's theoretical and practical contributions before turning to its limitations and offering suggestions for future research and practice.

5.2 Conclusion

Based on the research conducted, the following conclusions can be drawn:

1. Attitude toward electric vehicles has a positive and significant effect on purchase intention. The more favorably consumers judge EVs in terms of performance, benefits, and overall appeal, the stronger their intention to buy one.
2. Environmental concern has no significant effect on purchase intention. Being aware of, or worried about, environmental issues does not by itself lead consumers to a firmer intention to purchase an EV, which suggests that environmental motivation on its own is not enough to drive the decision.
3. Financial factors have a positive and significant effect on purchase intention. The more affordable and financially attractive an EV appears once price, incentives, and running costs are considered, the stronger the intention to buy.
4. Perceived behavioral control has a positive and significant effect on purchase intention. The more capable and well-resourced consumers feel to own and use an EV, including access to charging infrastructure and the relevant knowledge, the stronger their intention to purchase one.
5. Subjective norms have a positive and significant effect on purchase intention. The more encouragement or approval consumers perceive from family, peers, and their wider community regarding EVs, the more inclined they are to buy one.

6. Overall, the model demonstrates considerable explanatory power, with the five constructs together explaining 70% of the variance in purchase intention ($R^2 = 0.700$). Attitude, financial factors, perceived behavioral control, and subjective norms therefore emerge as substantial and meaningful drivers of EV purchase intention in DKI Jakarta, while environmental concern plays a comparatively negligible role.

5.3 Research Limitations

1. The sample was limited to respondents living in DKI Jakarta, so the findings may not reflect consumer behavior in other parts of Indonesia, where infrastructure readiness, income levels, and cultural attitudes toward EVs can differ considerably.
2. The study used non-probability purposive sampling. Although this made it easier to reach suitable respondents, it carries a risk of selection bias and limits how confidently the results can be generalized to the broader population.
3. The research measured self-reported purchase intention rather than actual buying behavior. The findings therefore reflect what consumers say they are prepared to do, not verified EV adoption.
4. The study was built solely around the extended TPB model, with attitude, perceived behavioral control, and subjective norms as its core constructs and environmental concern and financial factors added as extensions.
5. Only five predictor variables were included. Other potentially influential factors were left outside the model and may explain further variance in purchase intention.

5.4 Suggestions

In light of the conclusions above, a number of recommendations are offered for industry stakeholders and future researchers:

1. Strengthen attitude formation.

Because attitude toward EVs is the strongest predictor of purchase intention, manufacturers and dealers have good reason to invest in experiential marketing.

Test drives, hands-on showroom experiences, and honest performance comparisons with conventional vehicles can all help consumers form more favorable impressions.

2. Reframe environmental messaging.

Since environmental concern alone does not significantly influence purchase intention, sustainability campaigns should be paired with tangible, personally relevant benefits, whether cost savings, convenience, or status, rather than relying on environmental appeal by itself.

3. Improve financial accessibility.

Given the significant role of financial factors, industry players and policymakers should continue to broaden incentives such as subsidies, tax relief, and flexible financing options, and do more to make the long-term savings on fuel and maintenance clear to prospective buyers.

4. Expand enabling infrastructure.

As perceived behavioral control significantly affects purchase intention, continued investment in charging infrastructure, after-sales service networks, and consumer education on owning and maintaining an EV is recommended to lower the barriers people perceive.

5. Leverage social influence.

With subjective norms significantly shaping purchase intention, brands should consider community-based marketing, referral programs, and visible endorsement from early adopters to build social proof and make EV ownership feel normal within people's social circles.

Acting on these recommendations would help EV manufacturers, dealers, and policymakers turn consumer awareness into real purchase intention and speed up the wider uptake of electric vehicles across the Jakarta market.

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APPENDIX
RESEARCH QUESTIONNAIRE

**Electric Vehicle Purchase Decision Factors in DKI Jakarta Using
Enhanced Theory of Planned Behavior**

SECTION A: SCREENING QUESTIONS

A1. What is your age?

- ☐ Under 25 years (Exclude)
- ☐ 25-35 years
- ☐ 36-45 years
- ☐ 46-55 years
- ☐ Above 55 years (Exclude)

A2. Do you currently hold a valid driving license?

- ☐ Yes (Continue)
- ☐ No (Exclude)

A3. What is your monthly household income?

- ☐ Below IDR 10 million (Exclude)
- ☐ IDR 10-20 million
- ☐ IDR 20-30 million
- ☐ IDR 30-50 million
- ☐ Above IDR 50 million

A4. In which area of DKI Jakarta do you currently reside?

- ☐ Central Jakarta
- ☐ North Jakarta
- ☐ South Jakarta
- ☐ East Jakarta
- ☐ West Jakarta

A5. How familiar are you with electric vehicles (EVs)?

- ☐ Very familiar

- Somewhat familiar (Continue)
- Slightly familiar (Continue)
- Not familiar at all (Exclude)

SECTION B: MAIN SURVEY

Instructions: Please indicate your level of agreement with each statement using the scale below:

- 1 = Strongly Disagree,*
- 2 = Disagree,*
- 3 = Somewhat Disagree,*
- 4 = Neutral,*
- 5 = Somewhat Agree,*
- 6 = Agree,*
- 7 = Strongly Agree*

ATTITUDE TOWARD ELECTRIC VEHICLES (AEV) - 6 Items

AEV1. I have a favorable attitude toward electric vehicles

Scale: 1-2-3-4-5-6-7

AEV2. Electric vehicles are a good idea for urban transportation in Jakarta

Scale: 1-2-3-4-5-6-7

AEV3. I find electric vehicles appealing

Scale: 1-2-3-4-5-6-7

AEV4. Owning an electric vehicle would be beneficial for me

Scale: 1-2-3-4-5-6-7

AEV5. Electric vehicles represent the future of transportation

Scale: 1-2-3-4-5-6-7

AEV6. I believe electric vehicles are superior to conventional cars

Scale: 1-2-3-4-5-6-7

SUBJECTIVE NORMS (SN) - 4 Items

SN1. Most people whose opinions I value would approve of my EV purchase

Scale: 1-2-3-4-5-6-7

SN2. People who are important to me expect me to consider buying an electric vehicle

Scale: 1-2-3-4-5-6-7

SN3. I feel social pressure to consider environmentally friendly transportation

Scale: 1-2-3-4-5-6-7

SN4. My social circle views electric vehicle ownership positively

Scale: 1-2-3-4-5-6-7

PERCEIVED BEHAVIORAL CONTROL (PBC) - 5 Items

PBC1. I have the financial resources to purchase an electric vehicle

Scale: 1-2-3-4-5-6-7

PBC2. I have the knowledge needed to make an informed EV purchase decision

Scale: 1-2-3-4-5-6-7

PBC3. I have access to charging infrastructure in Jakarta

Scale: 1-2-3-4-5-6-7

PBC4. Purchasing an electric vehicle is entirely within my control

Scale: 1-2-3-4-5-6-7

PBC5. I am confident in my ability to operate and maintain an electric vehicle

Scale: 1-2-3-4-5-6-7

ENVIRONMENTAL CONCERN (EC) - 5 Items

EC1. I am concerned about air pollution in Jakarta

Scale: 1-2-3-4-5-6-7

EC2. Climate change is a serious problem that requires immediate action

Scale: 1-2-3-4-5-6-7

EC3. I feel responsible for reducing my environmental impact through transportation choices

Scale: 1-2-3-4-5-6-7

EC4. Electric vehicles can help improve air quality in Jakarta

Scale: 1-2-3-4-5-6-7

EC5. Environmental protection should be prioritized in vehicle purchase decisions

Scale: 1-2-3-4-5-6-7

FINANCIAL FACTORS (EF) - 4 Items

EF1. The recent VAT reduction makes electric vehicles more affordable

Scale: 1-2-3-4-5-6-7

EF2. Electric vehicles offer better long-term cost savings than conventional cars

Scale: 1-2-3-4-5-6-7

EF3. Government incentives make electric vehicles financially attractive

Scale: 1-2-3-4-5-6-7

EF4. The total cost of owning an EV is reasonable compared to conventional vehicles

Scale: 1-2-3-4-5-6-7

PURCHASE INTENTION (PI) - 4 Items

PI1. I intend to purchase an electric vehicle in the next 2 years

Scale: 1-2-3-4-5-6-7

PI2. I plan to consider electric vehicles as my next vehicle purchase

Scale: 1-2-3-4-5-6-7

PI3. The likelihood of purchasing an EV is high for me

Scale: 1-2-3-4-5-6-7

PI4. I am determined to make my next vehicle purchase an electric one

Scale: 1-2-3-4-5-6-7

SECTION C: DEMOGRAPHICS

D1. Gender:

- ☐ Male
- ☐ Female

D2. Highest education level:

- ☐ High School
- ☐ Diploma
- ☐ Bachelor's Degree
- ☐ Master's Degree
- ☐ Doctoral Degree

QUESTIONNAIRE SUMMARY

Construct	Items	Total Questions	Key Focus
Attitude toward EVs (AEV)	6	6	Overall evaluation of EVs
Subjective Norms (SN)	4	4	Social pressure
Perceived Behavioral Control (PBC)	5	5	Capability perceptions
Environmental Concern (EC)	5	5	Environmental awareness
Financial factors (EF)	4	4	Financial considerations
Purchase Intention (PI)	4	4	Likelihood to purchase
Demographics	2	2	Control variables
TOTAL MAIN SURVEY	30	30	Enhanced TPB Model

SCALE SOURCES AND RELIABILITY EXPECTATIONS

Construct	Adapted From	Expected Cronbach's α
AEV	Sharma & Shalender (2020), Low et al. (2025)	> 0.85
SN	Refor et al. (2023), Javid et al. (2022)	> 0.80
PBC	Sharma & Shalender (2020), Gayathiri & Ahamed (2025)	> 0.82
EC	Wang et al. (2016), Leksana et al. (2025)	> 0.88
EF	Falisa & Tricahyono (2025), He & Zhou (2022)	> 0.85
PI	Low et al. (2025), Refor et al. (2023)	> 0.90

