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End-of-Life Battery Disposal Behavior Electric Vehicles in Indonesian Using Structural Equation Model Approach

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ABSTRACT
The rapid adoption of electric vehicles (EVs) in Indonesia presents a future challenge in managing End-of-Life (EOL) battery waste, which is classified as hazardous and toxic material (B3). This study aims to develop a behavioral model analyzing factors influencing consumers' intention to return EOL EV batteries. Using an extended Theory of Planned Behavior (TPB) framework, this research examines eight latent variables: Attitude (AT), Subjective Norms (SN), Perceived Behavioral Control (PBC), Economic Incentive (EI), Environmental Awareness (EA), Broad Social Influence (BS), Government Policy (GP), and Battery Return Intention (BR). Data were collected through a survey of 173 EV owners in the Jabodetabek area and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results demonstrate that Attitude, Perceived Behavioral Control, and Economic Incentive significantly and positively influence Battery Return Intention. Furthermore, Environmental Awareness positively affects both Attitude and Subjective Norms, while Government Policy significantly enhances Perceived Behavioral Control. Interestingly, Subjective Norms showed no significant direct effect on Return Intention. The model explains 85.8% of the variance in return intention ($R^2 = 0.858$), indicating strong predictive power. These findings provide empirical evidence for policymakers and industry stakeholders to design effective strategies—including economic incentives, infrastructure development, and public awareness campaigns—to foster consumer participation in formal EOL battery recycling channels, supporting the circular economy transition in Indonesia's EV ecosystem.
Keywords: electric vehicle batteries; end-of-life; consumer behavior; theory of planned behavior; pls-sem

INTRODUCTION

The global transportation sector faces a critical challenge in carbon emissions, contributing 23% of total energy-related CO_2 emissions, with direct emissions exceeding 8 gigatons in 2022 (IEA, 2023). In Indonesia, the transportation sector accounts for approximately 30% of national greenhouse gas emissions (IESR, 2020). In response, electric vehicle (EV) adoption has been promoted as a sustainable alternative, with the Indonesian government implementing various policies, including tax reductions, purchase subsidies, and exemptions from odd-even traffic regulations (Pambudi & Juwono, 2023).

Indonesia has witnessed significant EV market growth since 2020. As of August 2024, two-wheeled EV units reached 167,864, while four-wheeled EVs reached 68,695 units (PT. Perusahaan Listrik Negara, 2025). The International Energy Agency projects that by 2030, EV sales will exceed 40% of total vehicle sales globally, based on current policies (IEA, 2025). This growth trajectory, while environmentally beneficial during the usage phase, creates an impending waste management challenge. Lithium-ion batteries, which power most EVs, have a lifespan of approximately 8-10 years (Phophongviwat & al., 2025). Considering Indonesia's EV adoption rate, studies estimate that EV battery waste will reach between 452,722 and 494,440 units by 2035 (Nurdini & al., 2025).

End-of-Life (EOL) EV batteries are classified as hazardous and toxic materials (B3) due to their heavy metal content, toxic chemicals, and reactive properties (Winslow et al., 2018). Improper disposal poses significant environmental risks, including soil and water contamination, as well as fire hazards accompanied by toxic gas release. While various recycling technologies exist—including direct recycling, pyrometallurgical, hydrometallurgical, and biometallurgical methods (Ali & al., 2025; Harper & al., 2019)—the success of any recycling system fundamentally depends on consumer participation in returning EOL batteries to formal collection channels.

Consumer disposal behavior, particularly regarding EOL battery return, is influenced by multiple factors, including economic considerations, social norms, environmental awareness, and policy frameworks (Guo & Huang, 2023). Understanding these behavioral determinants is crucial for designing effective collection strategies. The Theory of Planned Behavior (TPB) provides a robust theoretical foundation for analyzing such pro-environmental behaviors (Ajzen, 1991; Yuriev & al., 2020). TPB posits that behavioral intention is directly influenced by three core constructs: Attitude toward the behavior, Subjective Norms, and Perceived Behavioral Control.

However, studies specifically examining factors influencing Indonesian consumers' intentions to return EOL EV batteries remain scarce. Given Indonesia's unique socio-cultural context as a collectivist society, the interplay of economic incentives, environmental awareness, social influence, and government policy may differ from findings in other countries such as China, the United States, or European nations. China emphasizes comprehensive recycling infrastructure and Extended Producer Responsibility (EPR) enforcement (Ali & al., 2025), while the European Union implements strict circular economy regulations (Melin et al., 2021). Japan excels through second-life applications and collaborative government-industry approaches (Huo & al., 2017). Indonesia requires context-specific understanding to develop effective policies.

This research addresses this gap by developing a comprehensive behavioral model that integrates core TPB constructs with additional variables particularly relevant to the Indonesian context: Economic Incentive, Environmental Awareness, Broad Social Influence, and Government Policy. The novelty of this study lies in its empirical examination of these integrated factors within the specific setting of Indonesia's nascent EV market. It moves beyond simple direct-effect models to explore the mediating mechanisms through which external factors like policy and social influence shape individual intention.

Using Partial Least Squares Structural Equation Modeling (PLS-SEM), this research aims to: (1) identify and analyze the relationships between critical factors influencing EOL EV battery return intention among Indonesian consumers, and (2) formulate evidence-based recommendations for policymakers, manufacturers, and stakeholders. The primary objective is to provide actionable insights to enhance battery return rates and support the development of a circular economy within Indonesia's EV ecosystem. The benefit of this research is twofold: it contributes a theoretically grounded, context-specific behavioral model to the academic literature and offers practical, empirical guidance for designing effective collection strategies.

METHOD

Research Framework and Hypothesis Development

This study employs an extended Theory of Planned Behavior (TPB) framework incorporating eight latent variables. Figure 1 presents the conceptual model illustrating the hypothesized relationships among constructs.

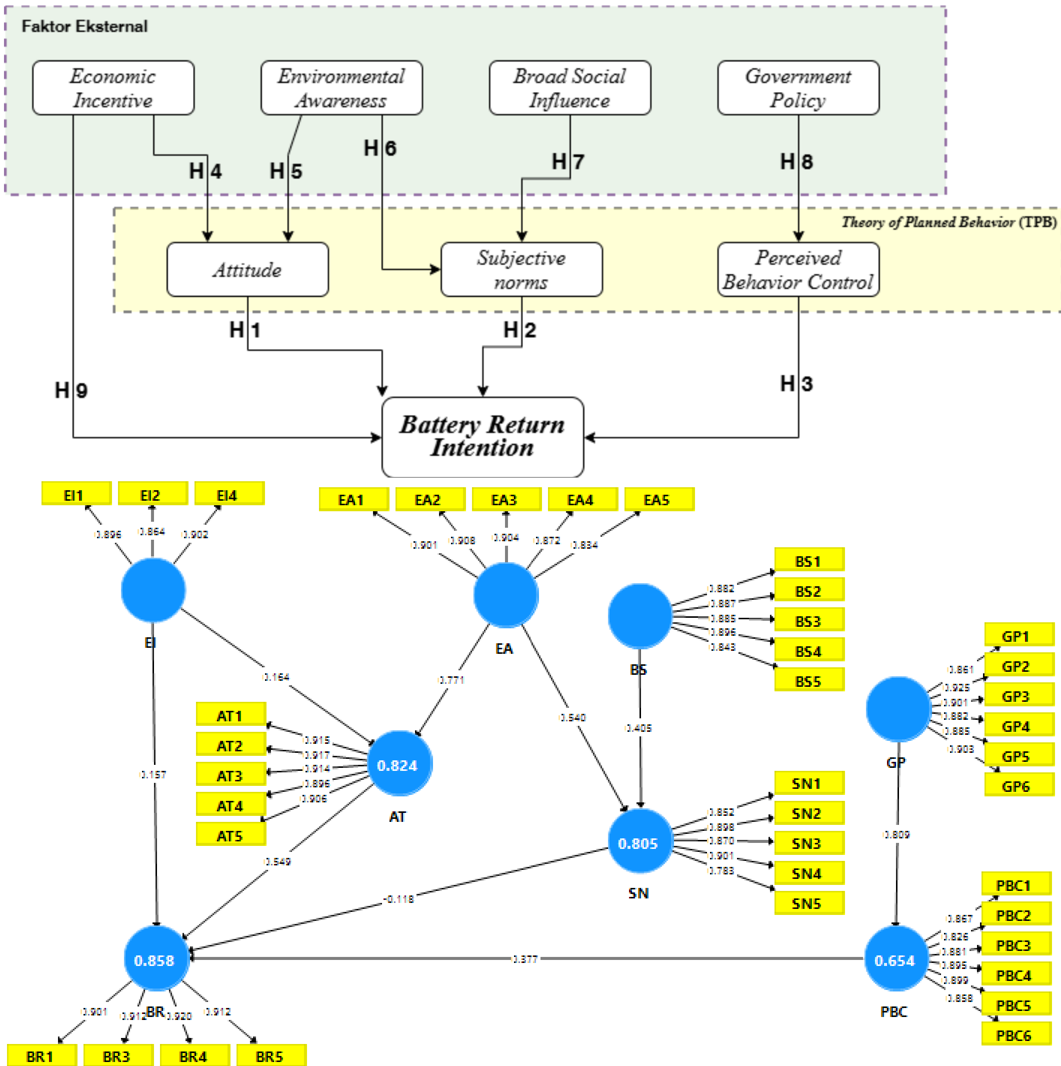

Figure 1. Conceptual Research Model

Table 1. Hypothesis Testing Results

Hypothesis	Description	Theoretical Basis
H1	Attitude positively influences Battery Return Intention	Sharma et al., 2024; D. Wang & al., 2024
H2	Subjective Norms positively influence Battery Return Intention	Ikram, 2022
H3	Perceived Behavior Control positively influences Battery Return Intention	Dong & Ge, 2022
H4	Economic Incentive positively influences Attitude	Guo & Huang, 2023
H5	Environmental Awareness positively influences Attitude	Mustafa et al., 2021
H6	Environmental Awareness positively influences Subjective Norms	Zhou & al., 2025
H7	Broad Social Influence positively influences Subjective Norms	Martínez-Sánchez et al., 2024
H8	Government Policy positively influences Perceived Behavior Control	Ali et al., 2025

Hypothesis	Description	Theoretical Basis
H9	Economic Incentive positively influences Battery Return Intention	Huang et al., 2024

Instrument Development

The questionnaire was developed based on validated instruments from previous studies, consisting of 39 indicators measuring eight latent constructs. Each indicator was measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Table 2 presents the constructs and their indicators.

Latent Variable	Number of Indicators	Source
Attitude (AT)	5	Dong & Ge, 2022; Tang et al., 2023
Subjective Norms (SN)	5	Ikram, 2022; Martínez-Sánchez et al., 2024
Perceived Behavior Control (PBC)	6	Ajzen, 1991; Sharma et al., 2024
Economic Incentive (EI)	3	Guo & Huang, 2023; Meng et al., 2019
Environmental Awareness (EA)	5	Mustafa et al., 2021; Islam et al., 2022
Broad Social Influence (BS)	5	Martínez-Sánchez et al., 2024
Government Policy (GP)	6	Ali et al., 2025
Battery Return Intention (BR)	4	Huang et al., 2024; Mustafa et al., 2021

Expert Validation and Pilot Test

The conceptual model, hypotheses, and indicators were validated by an expert from the Indonesian Automotive Industry Association (GAIKINDO) with over 30 years of experience. Expert validation resulted in refinement from 42 to 39 indicators. Subsequently, a pilot test was conducted with 30 EV owners to assess questionnaire validity and reliability. Corrected Item-Total Correlation (>0.361) was used for validity assessment, while Cronbach's Alpha (>0.6) assessed reliability. One indicator (PBC3) showed initial invalidity and was revised for improved clarity.

Data Collection

The target population was EV owners domiciled in the Jabodetabek area (Jakarta, Bogor, Depok, Tangerang, Bekasi), representing Indonesia's highest EV adoption region. Minimum sample size was determined using the inverse square root method (Kock, 2018) with 5% significance level and minimum path coefficient of 0.2, yielding a required minimum of 155 respondents. A mixed-method approach combining online (Google Forms distributed via social media platforms and EV communities) and offline (professional survey services) data collection was employed. Total responses collected were 367, with 173 valid responses after data cleaning.

Data Analysis Method

Data analysis employed Partial Least Square-Structural Equation Modeling (PLS-SEM) using SmartPLS 3.0 software. PLS-SEM was selected due to its suitability for exploratory research, predictive orientation, ability to handle complex models, and minimal distributional assumptions (Hair et al., 2019). Analysis followed a two-stage approach: (1) measurement model evaluation (outer model) assessing validity and reliability, and (2) structural model evaluation (inner model) testing hypothesized relationships.

Measurement model evaluation criteria included: 1) Convergent validity: factor loading > 0.7 and Average Variance Extracted (AVE) > 0.5. 2) Internal consistency reliability: Cronbach's Alpha > 0.6 and Composite Reliability (CR) > 0.7. 3) Discriminant validity: Fornell-Larcker criterion, cross-loadings, and Heterotrait-Monotrait Ratio (HTMT).

Structural model evaluation criteria included: 1) Path coefficients significance (t-statistics > 1.96; p-values < 0.05). 2) Coefficient of determination (R^2). 3) Effect size (f^2). 4) Predictive relevance (Q^2).

RESULTS AND DISCUSSION

Respondent Demographics

A total of 173 valid responses were analyzed. Table 3 presents respondent demographic characteristics.

Table 3. Respondent Demographic Profile

Characteristic	Category	Frequency	Percentage
Gender	Male	109	63.1%
	Female	64	36.9%
Age	< 25 years	12	6.9%
	25-35 years	83	48.0%
	36-45 years	64	37.0%
	46-55 years	9	5.2%
	> 55 years	5	2.9%
Domicile	Jakarta	45	26.0%
	Bogor	24	13.9%
	Depok	23	13.3%
	Tangerang	44	25.4%
	Bekasi	27	15.6%
	Others	10	5.8%
EV Ownership Duration	< 1 year	41	23.7%
	1-2 years	62	35.8%
	2-3 years	37	21.4%
	3-4 years	19	11.0%
	> 4 years	14	8.1%
EV Brand	BYD	47	27.2%
	Wuling	37	21.4%
	Hyundai	33	19.1%
	Chery	22	12.7%
	Others	34	19.6%

The sample is dominated by males (63.1%), aged 25-35 years (48.0%), with 1-2 years of EV ownership experience (35.8%). BYD (27.2%), Wuling (21.4%), and Hyundai (19.1%) are the most represented EV brands, reflecting Indonesia's current EV market composition.

Descriptive Statistics

Table 4 presents descriptive statistics for all constructs. Mean values ranged from 3.637 (Government Policy) to 4.042 (Battery Return Intention), indicating generally positive perceptions. Standard deviations ranged from 0.039 to 0.084 at the construct level. Skewness and kurtosis values within the -2 to +2 range indicate univariate normality of the data distribution (Brown, 2011).

Table 4. Descriptive Statistics of Constructs

Construct	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Attitude (AT)	4.010	0.042	0.002	-0.182	0.842
Subjective Norms (SN)	3.783	0.068	0.005	0.606	-3.254
Perceived Behavior Control (PBC)	3.926	0.084	0.007	0.434	-1.926
Economic Incentive (EI)	3.767	0.055	0.003	-0.930	0.000
Environmental Awareness (EA)	3.972	0.056	0.003	2.086	3.209
Broad Social Influence (BS)	3.738	0.075	0.006	-1.027	2.250
Government Policy (GP)	3.637	0.046	0.002	-0.282	0.219

Measurement Model Evaluation

Convergent Validity

Table 5 presents the convergent validity assessment results. All indicator loadings exceeded the recommended threshold of 0.7, ranging from 0.783 to 0.925. Average Variance Extracted (AVE) values for all constructs exceeded 0.5, ranging from 0.743 to 0.831. These results confirm satisfactory convergent validity (Hair et al., 2017).

Table 5. Convergent Validity and Reliability Results

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Attitude (AT)	0.948	0.960	0.827
Battery Return Intention (BR)	0.932	0.951	0.831
Broad Social Influence (BS)	0.926	0.944	0.772
Environmental Awareness (EA)	0.930	0.947	0.782
Economic Incentive (EI)	0.865	0.917	0.787
Government Policy (GP)	0.949	0.959	0.798
Perceived Behavior Control (PBC)	0.936	0.950	0.759
Subjective Norms (SN)	0.913	0.935	0.743

Reliability

Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability (CR). As shown in Table 5, Cronbach's Alpha values ranged from 0.865 to 0.949, exceeding the 0.6 threshold. Composite Reliability values ranged from 0.917 to 0.960, exceeding the 0.7 threshold. These results indicate high internal consistency and reliability of the measurement instruments.

Discriminant Validity

Discriminant validity was assessed using three criteria: Fornell-Larcker criterion, cross-loadings, and Heterotrait-Monotrait Ratio (HTMT).

The Fornell-Larcker criterion (Table 6) showed that the square root of AVE for each construct (diagonal values) was generally higher than correlations with other constructs. However, some correlations (e.g., EA with PBC = 0.917) slightly exceeded the square root of AVE, indicating potential discriminant validity concerns.

Table 6. Fornell-Larcker Criterion Results

	AT	BR	BS	EA	EI	GP	PBC	SN
AT	**0.909**							
BR	0.910	**0.911**						
BS	0.784	0.767	**0.879**					
EA	0.902	0.900	0.799	**0.884**				
EI	0.780	0.777	0.732	0.799	**0.887**			
GP	0.665	0.666	0.769	0.744	0.665	**0.893**		
PBC	0.900	0.885	0.822	0.917	0.762	0.809	**0.871**	
SN	0.854	0.814	0.836	0.863	0.805	0.794	0.894	**0.862**

Note: Diagonal values (bold) represent square root of AVE

Cross-loading analysis (Table 7) demonstrated that all indicators loaded highest on their respective constructs compared to other constructs, supporting discriminant validity.

Table 7. Cross-Loadings Analysis (Selected Indicators)

INDIKATOR	VARIABEL							
	AT	BR	BS	EA	EI	GP	PBC	SN
AT1	0.915	0.836	0.772	0.855	0.754	0.682	0.85	0.838
AT2	0.917	0.843	0.684	0.802	0.698	0.566	0.825	0.744
AT3	0.914	0.833	0.688	0.813	0.706	0.593	0.805	0.761
AT4	0.896	0.813	0.735	0.818	0.7	0.611	0.818	0.794
AT5	0.906	0.81	0.684	0.814	0.689	0.572	0.792	0.745
BR1	0.831	0.901	0.723	0.842	0.71	0.657	0.83	0.791
BR3	0.829	0.912	0.714	0.8	0.68	0.618	0.82	0.732
BR4	0.829	0.92	0.697	0.837	0.725	0.592	0.795	0.731
BR5	0.826	0.912	0.662	0.802	0.719	0.559	0.78	0.713
BS1	0.718	0.727	0.882	0.724	0.692	0.672	0.756	0.744
BS2	0.7	0.677	0.887	0.713	0.649	0.649	0.722	0.74
BS3	0.666	0.612	0.885	0.643	0.621	0.674	0.675	0.718
BS4	0.738	0.728	0.896	0.749	0.667	0.665	0.766	0.774
BS5	0.618	0.62	0.843	0.676	0.584	0.726	0.688	0.696
EA1	0.814	0.832	0.738	0.901	0.732	0.662	0.845	0.799
EA2	0.812	0.821	0.688	0.908	0.713	0.628	0.835	0.759
EA3	0.827	0.811	0.716	0.904	0.688	0.639	0.809	0.757
EA4	0.811	0.834	0.666	0.872	0.724	0.584	0.78	0.711
EA5	0.723	0.678	0.723	0.834	0.676	0.779	0.786	0.791
EI1	0.754	0.747	0.634	0.744	0.896	0.547	0.701	0.703
EI2	0.667	0.667	0.679	0.698	0.864	0.671	0.696	0.765
EI4	0.647	0.648	0.637	0.681	0.902	0.556	0.626	0.675
GP1	0.578	0.576	0.661	0.668	0.585	0.861	0.723	0.722

INDIKATOR	VARIABEL							
	AT	BR	BS	EA	EI	GP	PBC	SN
GP2	0.624	0.622	0.705	0.666	0.622	0.925	0.752	0.749
GP3	0.641	0.66	0.718	0.689	0.633	0.901	0.75	0.711
GP4	0.593	0.638	0.658	0.683	0.604	0.882	0.727	0.685
GP5	0.544	0.514	0.658	0.649	0.52	0.885	0.689	0.689
GP6	0.579	0.547	0.72	0.627	0.592	0.903	0.688	0.695
PBC1	0.799	0.778	0.697	0.776	0.649	0.655	0.867	0.776
PBC2	0.66	0.668	0.655	0.716	0.597	0.787	0.826	0.73
PBC3	0.87	0.852	0.751	0.852	0.698	0.627	0.881	0.768
PBC4	0.795	0.801	0.705	0.818	0.692	0.692	0.895	0.78
PBC5	0.827	0.81	0.773	0.846	0.669	0.697	0.899	0.785
PBC6	0.748	0.712	0.711	0.784	0.675	0.77	0.858	0.834
SN1	0.629	0.579	0.731	0.669	0.677	0.73	0.718	0.852
SN2	0.788	0.787	0.701	0.784	0.704	0.708	0.841	0.898
SN3	0.79	0.757	0.742	0.781	0.73	0.673	0.796	0.87
SN4	0.804	0.787	0.708	0.836	0.739	0.683	0.814	0.901
SN5	0.645	0.561	0.738	0.626	0.61	0.635	0.667	0.783

Note: Bold values indicate highest loadings

HTMT analysis (Table 8) showed some values exceeding the conservative threshold of 0.90, particularly for conceptually similar constructs (AT-BR: 0.968; EA-PBC: 0.982; PBC-SN: 0.963). Following (Henseler et al., 2015), HTMT inference using confidence intervals (Table 9) confirmed that the upper bounds of 95% confidence intervals did not include 1, supporting discriminant validity.

Table 8. HTMT Results

Variabel	AT	BR	BS	EA	EI	GP	PBC	SN
AT								
BR	0.968							
BS	0.835	0.824						
EA	0.961	0.966	0.86					
EI	0.858	0.862	0.817	0.889				
GP	0.700	0.706	0.822	0.792	0.735			
PBC	0.955	0.947	0.881	0.982	0.844	0.858		
SN	0.912	0.873	0.913	0.931	0.904	0.855	0.963	

Table 9. HTMT Confidence Intervals (95%)

Relationship	Original Sample (HTMT)	Sample Mean (M)	Bias	5.00%	95.00%
BR -> AT	0.968	0.967	-0.001	0.94	0.988
BS -> AT	0.836	0.834	-0.002	0.75	0.896
BS -> BR	0.824	0.822	-0.002	0.733	0.89
EA -> AT	0.96	0.96	0	0.924	0.984
EA -> BR	0.979	0.979	0	0.948	0.999
EA -> BS	0.836	0.833	-0.002	0.742	0.9

Relationship	Original Sample (HTMT)	Sample Mean (M)	Bias	5.00%	95.00%
EI -> AT	0.858	0.857	-0.001	0.77	0.916
EI -> BR	0.862	0.862	0	0.774	0.921
EI -> BS	0.817	0.816	-0.001	0.725	0.888
EI -> EA	0.877	0.877	0	0.788	0.936
GP -> AT	0.7	0.7	0	0.576	0.802
GP -> BR	0.706	0.707	0.001	0.584	0.806
GP -> BS	0.822	0.823	0.001	0.737	0.888
GP -> EA	0.738	0.738	0	0.623	0.828
GP -> EI	0.736	0.735	0	0.628	0.828
PBC -> AT	0.969	0.969	-0.001	0.938	0.993
PBC -> BR	0.957	0.956	-0.001	0.915	0.985
PBC -> BS	0.882	0.881	-0.001	0.8	0.941
PBC -> EA	0.973	0.973	0	0.947	0.995
PBC -> EI	0.847	0.846	-0.001	0.752	0.912
PBC -> GP	0.825	0.825	0.001	0.731	0.893
SN -> AT	0.91	0.909	-0.001	0.845	0.953
SN -> BR	0.887	0.886	-0.001	0.809	0.936
SN -> BS	0.88	0.88	-0.001	0.783	0.944
SN -> EA	0.908	0.907	-0.001	0.852	0.948
SN -> EI	0.901	0.901	0	0.833	0.95
SN -> GP	0.849	0.843	0	0.76	0.908
SN -> PBC	0.959	0.959	-0.001	0.919	0.985

Multicollinearity Assessment

Variance Inflation Factor (VIF) values for all structural relationships ranged from 1.000 to 7.575. Following (Hair et al., 2017), VIF values below 10 indicate no critical multicollinearity issues.

Structural Model Evaluation

Hypothesis Testing

Table 10 presents the path coefficients, t-statistics, p-values, and hypothesis testing results obtained through bootstrapping with 5,000 resamples.

Table 10. Hypothesis Testing Results

Hypothesis	Path	Path Coefficient	t-Statistics	p-Value	Result
H1	AT → BR	0.549	6.042	0.000	**Supported**
H2	SN → BR	-0.118	1.494	0.136	**Not Supported**
H3	PBC → BR	0.377	3.596	0.000	**Supported**
H4	EI → AT	0.164	2.308	0.021	**Supported**
H5	EA → AT	0.771	11.427	0.000	**Supported**
H6	EA → SN	0.540	7.320	0.000	**Supported**
H7	BS → SN	0.405	5.264	0.000	**Supported**
H8	GP → PBC	0.809	21.004	0.000	**Supported**
H9	EI → BR	0.157	2.812	0.005	**Supported**

Eight of the nine hypothesized relationships were supported at $p < 0.05$. Hypothesis H2 (Subjective Norms → Battery Return Intention) was not supported ($p = 0.136$), indicating that subjective norms do not significantly directly influence return intention in this context.

Coefficient of Determination (R^2)

The model explained substantial variance in endogenous constructs: 1) Battery Return Intention (BR): $R^2 = 0.858$. 2) Attitude (AT): $R^2 = 0.824$. 3) Subjective Norms (SN): $R^2 = 0.805$. 4) Perceived Behavior Control (PBC): $R^2 = 0.654$. Following (Hair et al., 2017), R^2 values exceeding 0.75 indicate substantial explanatory power. The model demonstrates strong predictive capability for all endogenous constructs.

Effect Size (f^2)

Effect sizes indicate the relative impact of each predictor construct: 1) EA → AT: $f^2 = 1.220$ (large effect). 2) GP → PBC: $f^2 = 1.893$ (large effect). 3) AT → BR: $f^2 = 0.353$ (medium-large effect). 4) EA → SN: $f^2 = 0.541$ (large effect). 5) BS → SN: $f^2 = 0.305$ (medium effect) 6) Other significant paths showed small effects (0.016-0.132)

Predictive Relevance (Q^2)

Stone-Geisser's Q^2 values obtained through blindfolding procedure: 1) BR: $Q^2 = 0.707$. 2) AT: $Q^2 = 0.676$. 3) SN: $Q^2 = 0.591$. 4) PBC: $Q^2 = 0.493$. All Q^2 values > 0 indicate the model has predictive relevance for all endogenous constructs.

Direct Determinants of Battery Return Intention

The findings reveal that Attitude ($\beta = 0.549$, $p < 0.001$) is the strongest direct predictor of Battery Return Intention, followed by Perceived Behavior Control ($\beta = 0.377$, $p < 0.001$) and Economic Incentive ($\beta = 0.157$, $p = 0.005$). These results align with TPB foundations (Ajzen, 1991) and previous studies on recycling behavior (Sharma & al., 2024; Dong & Ge, 2022).

The strong influence of Attitude indicates that Indonesian EV owners' intention to return EOL batteries is primarily driven by their positive evaluation of the behavior—viewing it as responsible, beneficial for the environment, and a moral obligation. This finding underscores the importance of cultivating positive attitudes through educational campaigns that emphasize environmental benefits and personal responsibility.

Perceived Behavior Control's significant influence highlights the critical role of enabling factors. Consumers who perceive themselves as having knowledge, time, accessibility to collection points, and ability to navigate return procedures demonstrate higher intention. This finding supports the work of (Murugan & Marisamynathan, 2024) and emphasizes the need for accessible infrastructure and clear information dissemination.

Economic Incentive's direct positive effect on intention (H9 supported) and indirect effect through Attitude (H4 supported) confirms that monetary considerations matter. This aligns with findings from China (Guo & Huang, 2023; Huang & al., 2024) demonstrating that financial incentives such as cashback, discounts, and trade-in programs effectively motivate participation in formal recycling channels. The relatively smaller direct effect compared to Attitude and PBC suggests that while economic incentives are important, they complement rather than replace intrinsic motivation.

The Non-Significant Role of Subjective Norms

The non-significant relationship between Subjective Norms and Battery Return Intention (H2: $\beta = -0.118$, $p = 0.136$) presents an interesting finding that contrasts with some TPB applications in recycling contexts (Ikram, 2022). Several explanations may account for this result.

First, EOL battery return may be perceived as a relatively novel behavior in Indonesia, with unclear social expectations. Unlike established recycling behaviors for household waste, social norms regarding EV battery disposal may not yet be crystallized in Indonesian society. Second, the behavior involves technical considerations (battery handling, transportation, designated collection points) that may override social pressure. Third, the collectivist nature of Indonesian society might manifest through other pathways—Environmental Awareness and Broad Social Influence significantly shape Subjective Norms (H6 and H7 supported), suggesting that social influences operate indirectly through norm formation rather than directly pressuring behavior.

This finding aligns with recent studies (Dong & Ge, 2022; Tang & al., 2023) suggesting that in emerging contexts, subjective norms may play a weaker direct role compared to individual attitudinal and control factors.

Antecedents of Attitude, Subjective Norms, and Perceived Behavior Control

Environmental Awareness emerged as the strongest predictor of Attitude ($\beta = 0.771$, $p < 0.001$) with a large effect size ($f^2 = 1.220$). This confirms that consumers with greater knowledge of environmental impacts, concern about pollution, and sense of responsibility develop more positive attitudes toward EOL battery return. This finding supports (Mustafa & al., 2021) and emphasizes the importance of environmental education in shaping pro-environmental dispositions.

Economic Incentive also significantly but modestly influences Attitude ($\beta = 0.164$, $p = 0.021$), indicating that perceived financial benefits contribute to positive evaluations. This aligns with behavioral economics perspectives suggesting that attitudes incorporate both intrinsic and extrinsic motivations (Guo & Huang, 2023).

For Subjective Norms formation, both Environmental Awareness ($\beta = 0.540$, $p < 0.001$) and Broad Social Influence ($\beta = 0.405$, $p < 0.001$) play significant roles. The substantial influence of Broad Social Influence—encompassing media campaigns, social media information, public figures, and national environmental trends—demonstrates that macro-level social forces shape individuals' perceptions of what constitutes socially appropriate behavior. This finding is particularly relevant for Indonesia's collectivist culture where community norms and social image matter (Venkatesh et al., 2012).

Government Policy demonstrates a remarkably strong influence on Perceived Behavior Control ($\beta = 0.809$, $p < 0.001$) with the largest effect size in the model ($f^2 = 1.893$). This finding underscores that clear regulations, accessible information, adequate infrastructure, and enforcement mechanisms significantly enhance consumers' perceived ability to return EOL batteries. The result strongly supports arguments by (Ali & al., 2025) and (S. Wang & al., 2020) regarding the enabling role of policy frameworks. It suggests that in Indonesia's developing EV ecosystem, government action is fundamental to creating conditions where consumers feel capable of participating in formal recycling.

Theoretical Contributions

This study makes several theoretical contributions. First, it extends TPB by integrating context-specific constructs relevant to EOL battery return behavior in a developing country setting. The successful integration of Economic Incentive, Environmental Awareness, Broad Social Influence, and Government Policy demonstrates that TPB provides a flexible framework accommodating additional predictors when theoretically justified (Yuriev & al., 2020).

Second, the findings reveal the mediating mechanisms through which external factors influence intention. Government Policy operates through Perceived Behavior Control, Environmental Awareness influences intention through Attitude and Subjective Norms, and Broad Social Influence operates through Subjective Norms. This nuanced understanding advances beyond simple direct-effect models.

Third, the non-significant direct effect of Subjective Norms challenges assumptions about social influence in collectivist cultures, suggesting that social norms may operate differently for novel, technically-complex behaviors compared to established daily practices.

Practical Implications for Policy and Industry

Based on the findings, several strategic recommendations emerge for stakeholders:

For Policymakers (Government):

1. **Strengthen enabling infrastructure**: Given PBC's strong influence mediated by Government Policy, prioritize development of accessible collection points, clear information systems, and streamlined procedures. The substantial GP→PBC effect ($\beta = 0.809$) indicates that policy action is the primary lever for enhancing perceived consumer capability.
2. **Implement tiered economic incentives**: Design incentive programs combining direct monetary compensation (cashback, discounts) with non-monetary recognition. The significant direct and indirect effects of EI suggest that well-designed incentive schemes can simultaneously enhance attitudes and directly motivate intention.
3. **Launch comprehensive awareness campaigns**: Target environmental education to leverage EA's strong influence on Attitude and Subjective Norms. Campaigns should emphasize environmental consequences of improper disposal, individual responsibility, and collective benefits of formal recycling.
4. **Develop clear regulatory frameworks**: Implement Extended Producer Responsibility (EPR) principles with clear sanctions for non-compliance, as policy clarity significantly enhances perceived behavioral control.

For Manufacturers and Industry Associations:

1. **Establish convenient collection networks**: Collaborate with dealerships (4S stores) and service centers to serve as accessible collection points. The significant PBC effect indicates that convenience matters.
2. **Integrate return programs with sales/service**: Offer trade-in programs when consumers purchase new EVs or during regular maintenance visits, leveraging existing touchpoints.
3. **Support consumer education**: Provide clear information about return procedures through multiple channels—websites, mobile applications, in-person consultations—to enhance perceived control.
4. **Participate in industry-wide standards**: Collaborate with government and other stakeholders to establish standardized battery traceability and collection systems.

For Community and Social Organizations:

1. **Leverage social influence channels**: Utilize media campaigns, social media influencers, and community leaders to shape positive norms around battery return, capitalizing on BS→SN influence.
2. **Build community-based initiatives**: Establish EV owner communities that share information and experiences about battery return, creating peer support networks.

CONCLUSION

This study successfully developed and empirically tested a comprehensive behavioral model to explain the factors influencing Indonesian EV owners' intentions to return End-of-Life (EOL) batteries. The findings confirm that return intention is directly and significantly shaped by positive personal attitudes, a strong sense of behavioral control, and the presence of economic incentives. Collectively, these three factors explain a substantial 85.8% of the variance in intention. A key theoretical contribution is the finding that subjective norms do not exert a direct influence on this specific behavior in the Indonesian context; instead, they are shaped by environmental awareness and broader social influences. The research also illuminates the critical antecedent pathways: environmental awareness is the primary driver of attitude formation, while government policy is the overwhelmingly dominant enabler of perceived behavioral control. This underscores the fact that in a developing EV market, a supportive and clear policy framework is not just helpful but fundamental to empowering consumer action.

For future research, several avenues are recommended. First, while this study focused on behavioral intention, future studies should employ longitudinal designs to track actual return behavior, thereby validating the intention-behavior link. Second, the sample was limited to the Jabodetabek area; expanding the geographical scope to include other Indonesian regions with varying levels of EV adoption and infrastructure would enhance the generalizability of the findings. Third, while the model demonstrated strong explanatory power, future research could explore the inclusion of additional factors, such as consumer trust in the recycling system, perceived risks associated with battery handling, and the influence of technological advancements in battery design on disposal perceptions. Finally, cross-cultural comparative studies between Indonesia and other Southeast Asian nations would provide valuable insights into regional similarities and differences, contributing to a more nuanced understanding of pro-environmental behavior in diverse cultural and economic settings.

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