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OPTIMIZING ELECTRIC TWO-WHEELER CHARGING INFRASTRUCTURE UNDER POLICY CREDIBILITY CONSTRAINTS: AN AGENT-BASED SIMULATION OF SUBURBAN TRANSPORT CORRIDORS

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***Abstract**:*

Inefficient sequencing of electric vehicle incentives and charging infrastructure investment can generate spatial redundancy in emerging-market transport systems. This study examines electric two-wheeler adoption in the Sleman-Bantul suburban transport corridor of Yogyakarta, Indonesia, where generous purchase subsidies and public charging expansion have not translated into significant market uptake. We develop a four-stage hybrid transport-planning framework combining Partial Least Squares Structural Equation Modeling, Classification and Regression Tree analysis, Agent-Based Modeling, and Genetic Algorithm optimization. Survey data from 1,362 suburban commuters were transformed into empirical agents and embedded in a geographically explicit OpenStreetMap-based commuting network to simulate 10-year diffusion under household charging constraints and dual home-work accessibility conditions. PLS-SEM identifies Policy Credibility as the strongest predictor of adoption intention, exceeding perceived economic value and infrastructure confidence. CART analysis reveals a non-compensatory threshold: commuters with a Policy Credibility index ≤ -0.46 are classified as late-market adopters regardless of economic or infrastructure advantages. The calibrated ABM shows that a Business-As-Usual scenario reaches only 10.94% adoption over ten years. Genetic Algorithm optimization identifies a resource-efficient infrastructure leverage point at 31 fast-charging units, achieving 53.35% adoption when combined with improved policy credibility, an IDR 9 million subsidy and 130 km battery range. Expanding the number of units from 31 to 46 raised the adoption rate by only 1.99 percentage points, indicating severe spatial saturation and overlapping charging catchments. These findings demonstrate that electric two-wheeler infrastructure planning in suburban transport corridors requires institutional credibility constraints to be incorporated before capital-intensive charging deployment. The study contributes a hybrid simulation-optimization framework for reducing fiscal misallocation and improving sustainable transport infrastructure planning.

Keywords: *Electric two-wheeler adoption, Policy credibility, Agent-based modeling, Infrastructure saturation, Non-compensatory decision-making*

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1. Introduction

1.1. The Policy Paradox in Electric Two-Wheeler Adoption

Governments pursuing rapid electrification of two-wheeled transport often deploy two policy instruments: direct purchase subsidies and public charging infrastructure expansion. Indonesia illustrates this pattern clearly. Under its 2022 Revised Nationally Determined Contribution (NDC), the country committed to a 31.89% unconditional reduction in greenhouse gas emissions by 2035, with the transport sector accounting for approximately 27% of national energy-related CO_2 emissions (Adityawarman et al., 2025; Nassar et al., 2023; Pranita & Sarjana, 2025; Putra et al., 2025). To meet these obligations, the government has established a target of 13 million electric motorcycles by 2030 and introduced an IDR 7 million per-unit purchase subsidy in 2023.

After three years into implementation, electric two-wheeler (EV2W) market penetration remains at less than 2% of total motorcycle sales. This gap between subsidy generosity and market response is not unique to Indonesia; similar stagnation has been observed in growing Southeast Asian markets despite comparable fiscal commitment (Chaniago et al., 2025; Chen et al., 2018; Cheng et al., 2018; Lin et al., 2025). The conventional policy response to underperformance is to raise subsidy value or expand charging infrastructure further. This study argues that both responses may be misdirected, because neither addresses what we identify as the binding constraint: the erosion of consumer trust in the durability of the policy environment itself.

1.2 Research Objectives and Hybrid Methodological Approach

This study addresses the EV2W policy paradox by conceptualizing institutional trust not as a compensatory variable, but as a non-compensatory gatekeeper. Consequently, the central research hypothesis of this study is formulated as follows: Policy Credibility operates as a non-compensatory threshold condition rather than a conventional linear determinant of EV2W adoption intention. Our objectives are to:

1. Evaluate the behavioral determinants of EV2W adoption among suburban commuters in emerging markets.
2. Extract non-linear decision rules to test the threshold effect of policy credibility.
3. Simulate a 10-year spatial diffusion dynamic accounting for real-world constraints (e.g., household electrical capacity).
4. Identify the cost-efficient leverage point between infrastructure expansion and policy design.

To overcome the limitations of linear technology-adoption models, we developed a sequential hybrid architecture. The analytical process begins with PLS-SEM to establish baseline causal relationships, which then feed into a CART algorithm to extract discrete, non-compensatory behavioral rules. This step explicitly addresses the cognitive overlap inherent in early-stage technology evaluation. These extracted rules are subsequently operationalized within a spatial Agent-Based Model (ABM) to simulate a 120-month diffusion trajectory across the Sleman-Bantul corridor. Ultimately, a Genetic Algorithm (GA) is applied to optimize the parameter space and pinpoint exact infrastructure saturation points. This transferable decision-support framework distinguishes between capital expenditure that accelerates adoption and expenditure that merely funds spatial redundancy.

2. Literature Review

Indonesian EV2W policy has been characterized by annual eligibility revisions, opaque subsidy disbursement processes, abrupt program suspensions, and the absence of multi-year legislative commitment. We term this pattern regulatory hysteresis: a condition in which repeated policy adjustment intended to improve program targeting instead degrades consumer trust in the state's capacity to honor a multi-year commitment. Because an EV2W purchase represents a 5–7 year asset commitment, consumers rationally discount subsidy value by their perceived probability of program discontinuation, a mechanism consistent with institutional economics literature on credible commitment (F. Wu et al., 2022; X. Wu et al., 2023). Under this framing, deploying capital into charging infrastructure before resolving the trust deficit risks creating underutilized assets instead of accelerating adoption.

This creates a testable hypothesis with direct fiscal consequences: if institutional distrust operates as a threshold condition rather than a graded influence, then infrastructure investment beyond a certain density will show diminishing returns regardless of subsidy value, because the underlying adoption

bottleneck is behavioral and institutional rather than physical.

2.1. Limitations of Compensatory Adoption Models and the Methodological Gap

Dominant technology-adoption frameworks the Technology Acceptance Model (TAM) and UTAUT2 model consumer decisions as compensatory: a deficit in one attribute (e.g., limited infrastructure) can be offset by a surplus in another (e.g., a large subsidy) (Cordero et al., 2025; Shetty & Rizwana, 2024). Institutional trust constructs, including policy credibility and infrastructure confidence, have recently begun to appear in EV adoption research (Adamashvili & Thrassou, 2024; Chonsalasin et al., 2024a; Saragih et al., 2026). However, these studies estimate the influence of institutional trust using the same compensatory and linear-additive logic applied to every other UTAUT2 construct, reporting at most only standardized path coefficient that describes an average, graded effect across the full sample.

This estimation strategy carries an unexamined assumption: that institutional distrust behaves like any other predictor, capable of being offset by sufficient improvement elsewhere in the decision calculus. No published study in this literature has tested whether this assumption is correct. If policy distrust instead operates as a non-compensatory threshold condition, a value below which no combination of price, performance, or infrastructure advantage alters the outcome, then every prior structural model estimating policy credibility as a linear path coefficient has systematically understated its practical decision weight, and every policy simulation built on such coefficients has misallocated resources toward levers that a distrustful segment will not respond to at any level. While measuring institutional trust is not inherently new, this study introduces a critical methodological pivot: rather than assuming linear behavior, we empirically test whether this construct acts as a non-compensatory behavioral gatekeeper. Furthermore, we translate these empirical thresholds into a calibrated spatial diffusion simulation to quantify the fiscal implications for infrastructure sequencing and integration, which were previously unexplored in Southeast Asian two-wheeler electrification policy.

3. Methodology

3.1. Research Design

This study adopted a sequential explanatory-predictive design with four analytical stages, each stage using the output of the preceding stage as its primary input. This architecture is deliberate: no single method in isolation can simultaneously (a) test theory-driven causal relationships, (b) detect non-linear behavioral thresholds, (c) simulate population-level diffusion over time, and (d) search a high-dimensional policy parameter space for a cost-efficient solution. The four stages are as follows:

1. **Partial Least Squares Structural Equation Modeling (PLS-SEM):** Estimates the strength and significance of hypothesized relationships between an extended UTAUT2 construct set and adoption intention, using cross-sectional survey data.
2. **Classification and Regression Tree (CART):** Converts the latent variable scores from Stage 1 into discrete, non-linear decision rules that capture threshold and interaction effects unavailable to linear structural models.
3. **Agent-Based Modeling (ABM):** Implements the CART-derived rules as micro-level agent behavior in a geographically explicit simulation of the Sleman-Bantul commuter corridor, projecting diffusion over a 120-month (10-year) horizon.
4. **Genetic Algorithm (GA) Optimization:** Searches the joint parameter space of policy credibility and public charging infrastructure density to identify the configuration that maximizes adoption per unit of infrastructure cost.

The sequential flow of data and the specific integration points between the statistical estimation and machine learning phases are visually mapped in Figure 1. It illustrates how empirical survey responses are systematically transformed into parameterized agent rules.

3.2. Population, Sample, and Study Setting

The population comprises commuters from Sleman Regency and Bantul Regency, two suburban regencies that structurally enveloping the urban core of Yogyakarta City, Indonesia (Figure 2). This corridor was selected for three reasons: (i) daily commute distances of 10–25 km fall within the practical range

of current EV2W battery technology; (ii) the population exhibits strong communal social structure, relevant to testing social-influence constructs; and (iii) the corridor represents a suburban commuter profile distinct from the megacity contexts (e.g., Jakarta) that dominate existing EV adoption literature (Iamtrakul & Klaylee, 2021; Kresnanto et al., 2025). Data collection targeted a minimum of 1,000 valid responses. The final sample comprised 1,362 valid respondents, collected through a combination of broad social media distribution and direct field survey of residents domiciled in Sleman and Bantul. Each respondent was later transformed on a strict 1-to-1 basis into an individual agent in the Stage 3 simulation (Section 2.6).

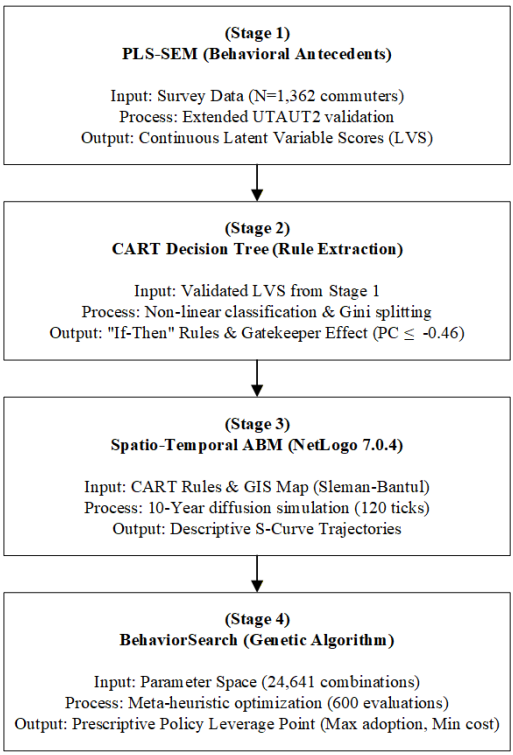

Fig. 1. The four-stage sequential hybrid methodology, detailing the data flow from structural estimation to multi-agent simulation and meta-heuristic optimization

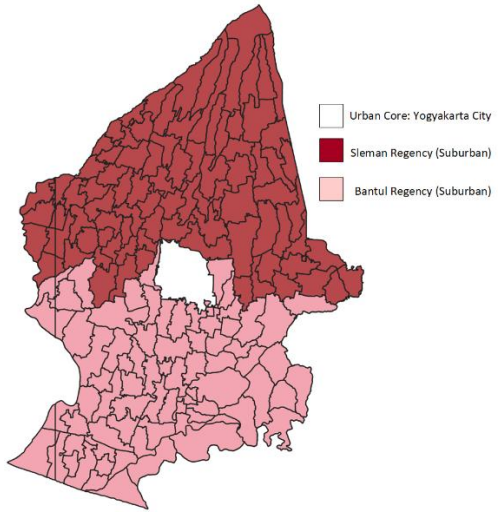

Fig. 2. Map of the study setting, illustrating the Sleman-Bantul suburban commuter corridor relative to the Yogyakarta City urban core.

Sample demographic characteristics are summarized as follows: 75.9% of respondents were aged 20–39; 53.1% held a bachelor's degree; and 49.5% reported monthly expenditure between IDR 2.5 and 5 million. Critically for the simulation calibration in Stage 3, household electrical capacity was distributed as follows: 450 VA (7.5%), 900 VA (40.8%), 1,300 VA (41.7%), 2,200 VA (7.4%), and >2,200 VA (2.6%). Notably, 48.3% of respondents (450–900 VA combined) operate at or below the 900 VA tier, a critical constraint directly incorporated into the ABM's home-charging feasibility parameter (Section 2.6).

The data collection process followed standard academic ethical protocols for human-subject research. Written informed consent was obtained from all 1,362 respondents before they initiated the survey. The survey instrument clearly stated the academic purpose of the data, the voluntary nature of participation, and guaranteed strict anonymity. No personally identifiable information (PII) was stored or mapped into the simulation environment; spatial attributes were aggregated and randomized within the respondents' reported sub-district boundaries to preserve privacy while maintaining macro-spatial commuting validity.

3.3. Construct Operationalization: Extended UTAUT2

The measurement instrument extends the UTAUT2 framework (Venkatesh et al., 2012) with two constructs identified in preliminary qualitative scoping as absent from standard technology-adoption models but theoretically central to subsidy-dependent adoption contexts: Policy Credibility (PC) and Infrastructure Confidence (IC). The measurement instrument synthesizes the UTAUT2 framework with specific institutional trust constructs. The complete operationalization of variables, measurement items, and their theoretical provenance are detailed in Table 1.

Note on terminology: the construct originally labeled "Price-Economy Value" in earlier drafts is standardized throughout this manuscript as Perceived Economic Value (PEV) to align with established consumer behavior nomenclature (Mehla et al., 2026; Venkatesh et al., 2012; Wang et al., 2023). A pilot test (n = 66; 35 valid responses after data cleaning) preceded full deployment. Results show the majority of indicators achieving loadings above 0.708 and AVE above 0.5. One adjustment followed: indicator PEV4, originally phrased as a negatively worded perceived-risk item, was reworded as a positively worded price-value item to improve cognitive consistency and reduce survey fatigue.

Table 1. Operationalization of variables, indicators, and supporting literature sources

Latent Variable	Operational Definition	Code	Measurement Items (Indicators)	Main References
Performance Expectancy (PE)	Perceived functional benefit of EV2W use	PE1 - PE4	**a. PE1:** I expect that using an electric motorcycle will make my daily mobility more efficient. **b. PE2:** I expect an electric motorcycle to be highly beneficial in supporting my daily travel activities. **c. PE3:** I expect that using an electric motorcycle can help reduce my monthly transportation expenses (e.g., fuel costs). **d. PE4:** Overall, I expect an electric motorcycle to offer better functionality for my needs compared to a gasoline motorcycle.	(Venkatesh et al., 2012), (Shofi & Salehudin, 2025), (Hidayatullah et al., 2025)
Effort Expectancy (EE)	Perceived ease of use and maintenance	EE1 - EE4	**a. EE1:** I expect that learning how to ride an electric motorcycle will be very easy for me. **b. EE2:** I expect that operating the basic features of an electric motorcycle (such as charging the battery) will be easy for me. **c. EE3:** I expect that interacting with an electric motorcycle (from starting the engine to daily maintenance) will be clear and understandable. **d. EE4:** I expect that I will not encounter any significant difficulties if I switch to using an electric motorcycle.	(Venkatesh et al., 2012), (Shofi and Salehudin, 2025), (Hidayatullah et al., 2025)
Hedonic Motivation (HM)	Perceived enjoyment or pride associated with EV2W use	HM1-HM4	**a. HM1:** Imagining or riding an electric motorcycle sounds enjoyable to me. **b. HM2:** I feel enthusiastic and interested in trying an electric motorcycle in my neighborhood. **c. HM3:** I believe that an electric motorcycle provides an entertaining riding experience (e.g., quiet sound, new technology). **d. HM4:** I believe that using an eco-friendly vehicle like an electric motorcycle provides a distinct sense of pride.	(Venkatesh et al., 2012), (Manutworakit & Choocharukul, 2022), (Hidayatullah et al., 2025)

Latent Variable	Operational Definition	Code	Measurement Items (Indicators)	Main References
Communal Identity and Norms (CIN)	Perceived environmental support and group conformity pressure	CIN1 - CIN4	**a. CIN1:** I believe that using an electric motorcycle will enhance my positive image in my neighborhood. **b. CIN2:** Many people in my social circle have started talking about or recommending the use of electric motorcycles. **c. CIN3:** I feel more proud to use a vehicle that is considered innovative by my community. **d. CIN4:** The expectations of people close to me or community leaders influence me to consider an electric motorcycle.	(Venkatesh et al., 2012), (Shofi and Salehudin, 2025), (Ajao et al., 2024; Alsalmi et al., 2025; Christian et al., 2025; Sakshi et al., 2025)
Habit (HT)	Automatic tendency to continue using conventional motorcycles	HT1 - HT4	**a. HT1:** I rely heavily on a motorcycle as my primary mode of transportation; it is an absolute necessity for my daily activities. **b. HT2:** I am confident that switching to an electric motorcycle will not disrupt my daily rhythm and will quickly integrate into my new lifestyle. **c. HT3:** Whenever I have to travel, using a motorcycle is always the automatic and instant decision that comes to my mind. **d. HT4:** Riding a motorcycle has become a natural routine for me, and this convenience will remain the same if I switch to an electric motorcycle.	(Venkatesh et al., 2012), (Shofi and Salehudin, 2025)
Perceived Economic Value (PEV)	Purchase price considerations and long-term financial risk perception	PEV1 - PEV4	**a. PEV1:** I believe the current purchase price of an electric motorcycle is worth the benefits and technology it offers. **b. PEV2:** I am confident that routine expenses for charging an electric motorcycle battery will be much more economical compared to the budget for purchasing gasoline. **c. PEV3:** I expect that the periodic maintenance costs of an electric motorcycle will be more affordable than a conventional motorcycle. **d. PEV4:** Overall, I feel that owning an electric motorcycle is a profitable long-term financial decision.	(Venkatesh et al., 2012), (Shofi and Salehudin, 2025), (Manutworakit and Choocharukul, 2022), (Baglee & Mills, 2026; Ma et al., 2023)
Infrastructure Confidence (IC)	Trust in the reliability and availability of supporting infrastructure	IC1 - IC4	**a. IC1:** Electric motorcycle charging or battery swap stations are very easy to find around my neighborhood or sub-district. **b. IC2:** I feel it would be easy to find an authorized electric motorcycle repair shop near my residence if a breakdown occurs. **c. IC3:** I trust that my home's electrical grid can safely support charging an electric motorcycle. **d. IC4:** I feel at ease because the electric motorcycle ecosystem (such as the distribution of charging/swap stations along my routes and the availability of authorized repair shops) is ready to support my daily activities.	(Venkatesh et al., 2012), (Adamashvili & Thrassou, 2024; Ahmad et al., 2024; Dwyer et al., 2021; Syauqi & Aprilia, 2025), (Ajao et al., 2024)

Latent Variable	Operational Definition	Code	Measurement Items (Indicators)	Main References
Policy Credibility (PC)	Trust in the consistency and durability of government incentives	PC1 - PC4	**a. PC1:** I trust that the government's subsidy program for electric motorcycles will continue transparently. **b. PC2:** Government regulations regarding the use of electric vehicles in Indonesia are clear and trustworthy. **c. PC3:** I am confident that the government will provide long-term protection guarantees for electric motorcycle users. **d. PC4:** Government promises regarding tax facilitation and incentives for electric motorcycles strongly influence my interest.	(Chonsalasin et al., 2024b; Saragih et al., 2026; Yan et al., 2019)
Behavioral Intention (BI)	Individual intent to seek information on and purchase an EV2W	BI1 - BI4	**a. BI1:** I intend to start using an electric motorcycle in the near future. **b. BI2:** I plan to make an electric motorcycle my primary vehicle in the future. **c. BI3:** I will seriously consider choosing an electric motorcycle when purchasing my next two-wheeled vehicle. **d. BI4:** I will recommend the use of electric motorcycles to family and friends in my environment.	Venkatesh et al. (2012); (Boison et al., 2022; Lamari, 2025; Lampo et al., 2023; Shofi & Salehudin, 2025; Zhang et al., 2024)

3.4. Stage 1: PLS-SEM Estimation

Structural equation modeling was conducted in SmartPLS 4, following the standard two-stage evaluation protocol:

Measurement model (outer model): Convergent validity was assessed via outer loadings (threshold > 0.7) and Average Variance Extracted (AVE > 0.5). Discriminant validity was assessed using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT < 0.9). Internal consistency reliability was assessed via Cronbach's Alpha and Composite Reliability (both > 0.7).

Structural model (inner model): Hypotheses were tested via path coefficients (β), significance levels (p-values, bootstrapped with 5,000 resamples), and model fit indicators R^2 and Q^2 (predictive relevance, via blindfolding procedure).

3.5. Stage 2: CART Rule Extraction

3.5.1. Rationale for Combining PLS-SEM with CART

PLS-SEM estimates average, linear, and additive relationships between constructs and behavioral intention. This estimation strategy assumes compensatory decision-making: a low score on one predictor can be offset by a high score on another, and the model reports a single global coefficient per path regardless of where a respondent sits in the distribution of that predictor. This assumption is well suited to determining *which* constructs matter on average, but structurally incapable of detecting *whether* a construct operates as a threshold condition, a value below which the outcome is fixed regardless of all other inputs.

CART addresses this limitation directly. As a recursive partitioning algorithm, CART does not assume linearity or compensability; it evaluates the data for the single split point that most reduces outcome impurity, then repeats this search within each resulting partition. This allows CART to surface asymmetric, non-compensatory patterns such as a gatekeeper effect, where one construct disqualifies an outcome regardless of all other predictor values that a linear structural coefficient would average away or suppress entirely. Using PLS-SEM alone would have reported Policy Credibility as "an important predictor with β = 0.297." It would not have revealed that respondents below a specific PC threshold are behaviorally locked into the Laggard category irrespective of their scores on price, performance, or infrastructure constructs. The sequential coupling of

these methods is methodologically deliberate. Extracting Latent Variable Scores (LVS) via PLS-SEM isolates the true construct variance from measurement noise, providing cleaner continuous inputs than raw item averages. CART is subsequently applied to these refined scores because linear path coefficients cannot be programmed as actionable, procedural logic for autonomous agents in a simulation. CART bridges this gap by translating the continuous latent thresholds into discrete, non-compensatory 'if-then' heuristics, providing a robust operational foundation for the agent-based model (Brandmaier et al., 2013; Richter & Tudoran, 2024; Serang et al., 2021).

3.5.2. CART Implementation

Input: Latent variable scores (LVS) extracted from the Stage 1 PLS-SEM model, used as continuous predictor features.

Target variable: Target variable and Discretization: To execute the CART algorithm, the continuous Latent Variable Scores (LVS) for Behavioral Intention (BI) required discretization. To eliminate subjective bias, the cut-off values were determined entirely independent of the CART analysis, strictly anchored to the standard normal distribution percentiles of Rogers' (2003) Diffusion of Innovations theoretical curve. The continuous Z-scores were mapped into five ordinal categories (Rogers, 2003):

a. **Innovators:** BI > 1.262 (Actual: 4.33%, Theoretical: 2.5%).
b. **Early Adopters:** 0.739 < BI ≤ 1.262 (Actual: 12.70%, Theoretical: 13.5%).
c. **Early Majority:** 0.251 < BI ≤ 0.739 (Actual: 32.97%, Theoretical: 34.0%).
d. **Late Majority:** −0.918 < BI ≤ 0.251 (Actual: 34.58%, Theoretical: 34.0%).
e. **Laggards:** BI ≤ −0.918 (Actual: 15.42%, Theoretical: 16.0%).

This theoretical mapping produced an actual sample distribution highly consistent with Rogers' ideal curve (maxium deviation of +1.83%), confirming the empirical validity of the thresholds prior to machine learning execution.

Splitting criterion: Gini impurity, selected for its computational efficiency and standard use in multi-class classification trees.

Class imbalance handling: The five-class target distribution was substantially imbalanced, as is typical of adopter-category data, where Innovators and Early Adopters are inherently underrepresented compared to early/Late Majority segments. The algorithm was therefore executed with class_weight='balanced', which inversely weights each class by its frequency in the training data, preventing the tree from optimizing solely for majority-class accuracy at the expense of minority-class (e.g., Innovator) rule extraction.

Validation: 5-fold stratified cross-validation was applied to preserve class proportions across folds and produce a stable estimate of out-of-sample classification performance.

3.6. Stage 3: Agent-Based Modeling (ABM)

The ABM was constructed in NetLogo 7.0.4 following the ODD (Overview, Design concepts, Details) protocol.

Agent initialization - Empirical Row Bootstrapping: Rather than generating agent attributes from random normal or synthetic distributions, a common but limiting practice that discards real inter-variable dependencies, each of the 1,362 survey respondents, was mapped directly, on a 1-to-1 row basis, to a single simulated agent. Each agent's full attribute vector (all UTAUT2 construct scores, demographic variables, and geographic origin-destination coordinates) was read directly from that respondent's actual survey row. This "empirical row bootstrapping" approach preserves the true empirical correlation matrix between constructs, for instance, the real joint distribution of low PC and low IC observed in the raw data, which synthetic distribution-based agent generation would otherwise flatten or distort.

Spatial environment and GIS topology: The simulation environment operates on an explicit geospatial topology of the Sleman-Bantul corridor. The underlying road network and boundary geometry were extracted from OpenStreetMap (OSM) data and validated against spatial records from the Indonesian Central Bureau of Statistics (BPS). Rather than randomly distributing charging nodes, the initial infrastructure placement in the ABM reflects the actual coordinates of existing state-owned (PLN) charging stations within the region. Each agent is evaluated using a dual-node spatial approach: both the agent's home coordinate and work coordinate distributed proportionally based on BPS commuter density data, are independently assessed against proximity to the nearest public fast-charging (SPKLU) node along the mapped arterial network.

Behavioral update logic: At each monthly tick, agents update their adoption readiness according to the CART-derived decision rules (Section 2.5.2), combined with a dynamic social-influence term. The Communal Identity and Norms (CIN) construct is treated as dynamic rather than static: it updates based on the observed adoption state of other agents within a defined spatial radius, operationalizing social proof effects reported in the survey (e.g., the 55.9% of respondents indicating a 3–8 person adoption threshold in their environment as a precondition for their own purchase).

Simulation horizon: The model runs for 120 ticks (1 tick = 1 month), reflecting the 5–10 year asset lifecycle of an EV2W and the requisite credible-commitment horizon. Crucially, the Policy Credibility (PC) attribute for each agent is calibrated to its empirical t=0 value and held strictly exogenous across the baseline simulation. This static configuration is a deliberate analytical boundary condition, not a predictive claim about future government action. By isolating the current cross-sectional trust deficit, we empirically demonstrate the long-term diffusion consequences of persistent regulatory hysteresis, establishing a baseline against which policy intervention scenarios (tested via GA in Stage 4) can be rigorously measured.

Model Logic and ODD Protocol Summary: Following the ODD (Overview, Design concepts, Details) protocol, the ABM execution is governed by physical constraints and the CART-derived pseudocode. Physically, agents with household electrical capacities of ≤ 900 VA are permanently restricted from home charging, and agents possessing conventional motorcycles younger than 48 months delay adoption to adhere to realistic replacement cycles. Cognitively, at each tick, agents execute the following continuous logical evaluation based on the CART thresholds:

IF policy-credibility <= -0.46:
IF (policy-credibility * effective-IC) > 0.86 [set readiness "Laggard"]
ELSE IF policy-credibility > -0.46:
IF effective-IC <= 0.67 AND effort-expectancy <= 0.02 [set readiness "Late Majority"]
IF effective-IC > 0.67 AND (policy-credibility * effective-IC) > 0.82 [set readiness "Early Adopter"]

Final adoption status is a convergence of this static cognitive readiness, dual-node spatial distance evaluation, and a dynamic intention-to-behavior probability conversion rate (1%–6% monthly).

3.7. Stage 4: Genetic Algorithm Optimization

To identify the theoretical infrastructure saturation points, the optimization process utilized a standard Genetic Algorithm architecture. The specific search space constraints and evolutionary parameters applied to the behavior search are summarized in Table 2.

Table 2. Genetic Algorithm (GA) Optimization Parameters

Parameter	Value
Algorithm type	Standard Genetic Algorithm
Population size	30
Number of generations	20
Stochastic replications per evaluation	3
Search space	Policy Credibility index (0–3) × SPKLU unit count (5–50)
Objective function	Maximize 120-month cumulative EV2W adoption rate

Each candidate solution (a specific PC–SPKLU combination) was evaluated across 3 stochastic ABM replications to account for simulation stochasticity, with fitness scored as mean adoption rate across replications. The GA iteratively evolves the population across 20 generations via selection, crossover, and mutation operators standard to BehaviorSearch's implementation, converging toward the parameter combination that maximizes adoption while allowing identification of the marginal cost-efficiency frontier reported in Section 3. The specific optimization objective was to maximize the cumulative EV2W adoption rate at tick 120. To handle stochasticity, the algorithm evaluated 205 candidate parameter combinations, each replicated 3 times (totaling 615 executions), ensuring the identified optimums represent stable structural limits rather than random spatial outliers.

4. Results

4.1. Measurement Model (Outer Model) Evaluation

Before evaluating the structural paths, the measurement model was thoroughly assessed for convergent validity, internal consistency reliability, discriminant validity, and indicator collinearity. As

summarized in Table 3, all 36 indicators exhibited outer loadings above the 0.70 threshold (ranging from 0.796 to 0.882) and the Average Variance Extracted (AVE) for all constructs exceeds the 0.50 minimum (ranging from 0.673 to 0.738). Internal consistency is robust, with Cronbach's alpha (0.838–0.882) and Composite Reliability (0.892–0.919) fully satisfying the 0.70 criteria. Outer collinearity statistics (VIF) ranges from 1.715 to 2.497, confirming the absence of indicator-level redundancy.

Table 3. Measurement Model Construct Reliability and Validity

Construct	Indicator	Outer Loading	Indicator VIF	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy (PE)	PE1	0.882	2.428	0.854	0.902	0.696
	PE2	0.823	1.888			
	PE3	0.803	1.808			
	PE4	0.827	1.896			
Effort Expectancy (EE)	EE1	0.812	1.84	0.842	0.894	0.678
	EE2	0.819	1.834			
	EE3	0.831	1.894			
	EE4	0.831	1.811			
Hedonic Motivation (HM)	HM1	0.854	2.149	0.874	0.914	0.726
	HM2	0.862	2.251			
	HM3	0.837	2.038			
	HM4	0.855	2.165			
Communal Identity & Norms (CIN)	CIN1	0.826	1.944	0.86	0.905	0.704
	CIN2	0.851	2.061			
	CIN3	0.829	1.92			
	CIN4	0.849	2.095			
Habit (HT)	HT1	0.834	1.944	0.84	0.893	0.676
	HT2	0.838	1.844			
	HT3	0.796	1.732			
	HT4	0.819	1.822			
Perceived Economic Value (PEV)	PEV1	0.801	1.715	0.838	0.892	0.673
	PEV2	0.823	1.858			
	PEV3	0.821	1.862			
	PEV4	0.836	1.902			
Infrastructure Confidence (IC)	IC1	0.869	2.455	0.882	0.919	0.738
	IC2	0.876	2.497			
	IC3	0.826	1.925			
	IC4	0.865	2.295			
Policy Credibility (PC)	PC1	0.849	2.123	0.876	0.915	0.73
	PC2	0.862	2.293			
	PC3	0.872	2.394			
	PC4	0.833	1.969			
Behavioral Intention (BI)	BI1	0.827	1.947	0.876	0.915	0.729
	BI2	0.842	2.064			
	BI3	0.865	2.31			
	BI4	0.88	2.47			

Discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT). While most construct pairs fell below the 0.85 threshold, four pairs exceeded 1.0: HT–EE (1.021), HM–CIN (1.003), PEV–HT (1.004), and PEV–CIN (1.015). This lack of strict discriminant validity critically affects the structural model interpretation. It indicates that pre-experiential commuters evaluate EV2Ws through generalized, overlapping cognitive schemas rather than distinct attribute dimensions. Consequently, the non-significance of specific constructs in the inner model does not imply irrelevance but rather reflects variance suppression due to empirical overlap. Inner model Variance Inflation Factor (VIF) diagnostics confirmed this structural limitation, yielding values exceeding 5 (e.g., CIN = 6.937, PEV = 6.168). This limitation forms the precise methodological justification for transitioning to the CART algorithm in Stage 2, which does not assume predictor independence.

4.2. Structural Model (Inner Model) Evaluation

The structural model demonstrates strong explanatory and predictive power. Behavioral Intention (BI) is explained at $R^2 = 0.786$. The Q^2 value of 0.576, obtained through the blindfolding procedure, confirms strong predictive relevance. Of the ten hypothesized paths, six were statistically supported. The rejected paths Effort Expectancy (EE → BI, $\beta = 0.039$, $p = 0.420$), Habit (HT → BI, $\beta = -0.078$, $p = 0.090$), Communal Identity and Norms (CIN → BI, $\beta = 0.034$, $p = 0.438$), and the PC × IC interaction ($\beta = -0.055$, $p = 0.077$) should be interpreted cautiously due to the aforementioned variance suppression. The full structural model results, detailing the bootstrapping evaluation (5,000 resamples) for all hypothesized paths, are presented in Table 3.

The lack of strict discriminant validity among specific construct pairs (e.g., HT–EE and HM–CIN) critically affects how these structural path coefficients must be interpreted. Specifically, the non-significance of Effort Expectancy, Habit, and Communal Identity in the structural model (H2, H4, H5) should not be interpreted as these factors being entirely irrelevant to EV2W adoption. Instead, due to their high empirical overlap, their unique predictive variances are conflated and statistically suppressed by the dominant constructs. This indicates that at this pre-experiential stage of technology adoption, respondents evaluate EV2Ws through generalized, overlapping cognitive schemas rather than distinct attribute dimensions. While Table 3 confirms the primacy of institutional trust over economic variables, the linear structural model cannot isolate the non-compensatory behavioral thresholds hidden within these overlapping constructs.

4.3. Multi-Group Analysis: Demographic Heterogeneity in Adoption Drivers

Multi-Group Analysis (MGA) was conducted to test whether the strength of key structural paths varies systematically across demographic segments. Three heterogeneities warrant explicit attention, as each carries distinct implications for targeted policy communication.

Table 4. Structural Model Hypothesis Testing Results (Bootstrapping 5,000 subsamples)

Hypothesis	Hypothesis Path	β	Mean	t-stat	p-value	Decision
H1	Performance Expectancy (PE) → BI	0.187	0.184	3.141	0.002	Supported
H2	Effort Expectancy (EE) → BI	0.039	0.037	0.807	0.420	Not Supported
H3	Hedonic Motivation (HM) → BI	0.171	0.171	3.906	<0.001	Supported
H4	Habit (HT) → BI	−0.078	−0.075	1.696	0.090	Not Supported
H5	Communal Identity & Norms (CIN) → BI	0.034	0.035	0.775	0.438	Not Supported
H6	Infrastructure Confidence (IC) → BI	0.216	0.219	6.042	<0.001	Supported
H7	Perceived Economic Value (PEV) → BI	0.118	0.118	2.865	0.004	Supported
H8	Policy Credibility (PC) → BI	0.297	0.296	6.475	<0.001	Supported
H9	PC × PEV → BI (Moderation)	0.062	0.063	2.120	0.034	Supported
H10	PC × IC → BI (Moderation)	−0.055	−0.055	1.767	0.077	Not Supported

Gender and Perceived Economic Value. PEV is a strong, significant predictor of adoption intention among male respondents (β = 0.235) but is statistically insignificant and directionally negative among female respondents (β = −0.051). This divergence indicates that price-based messaging, total cost of ownership calculations, fuel savings projections, and subsidy value framing are likely to be effective for male commuters but largely inert as a persuasion strategy for female commuters, who appear to weigh adoption on a different set of criteria not captured by economic framing alone.

Age and Policy Credibility. Policy Credibility exerts a substantially stronger effect among commuters aged 40 and above (β = 0.449) than in the sample overall (β = 0.297). This subgroup appears disproportionately sensitive to institutional trust signals, plausibly reflecting greater cumulative exposure to prior policy reversal or programmatic inconsistency over a longer observation window of government behavior. For this segment, the Gatekeeper Effect identified in Section 3.3 is likely to bind at a higher rate than in the sample average.

Driving Experience and Habit. The Habit (HT) construct, non-significant in the pooled model (β = −0.078, p = 0.090), emerges as a significant negative barrier specifically among riders with more than five years of motorcycle riding experience. Less experienced riders show no comparable habit-driven resistance. This indicates that habitual resistance to EV2W adoption is not a universal behavioral constant but a function of accumulated conventional-motorcycle usage history a barrier that strengthens with tenure rather than existing uniformly across the population.

No significant subgroup differences were detected by commute distance, suggesting that the determinants identified in this study operate consistently regardless of daily travel distance within the 10–25 km suburban range characteristic of this corridor. The significant deviations in path coefficients across key demographic subgroups, which directly inform targeted communication strategies, are reported in Table 5.

Table 5. Multi-Group Analysis (MGA) Significant Differences

Demographic Variable	Comparison	Path	β Group1	β Group2	Δβ	t-value	p-value	Significance
Gender	Male vs. Female	PEV→BI	0.235	−0.051	0.287	4.706	<0.001	Significant
Age	≤29 yrs vs 30–39 yrs	HT→BI	−0.007	−0.174	0.167	2.451	0.014	Significant
Age	30–39 yrs vs ≥40 yrs	IC→BI	0.293	0.102	0.191	2.422	0.016	Significant
Age	30–39 yrs vs ≥40 yrs	PEV→BI	0.195	−0.082	0.278	3.037	0.002	Significant
Age	30–39 yrs vs ≥40 yrs	PC→BI	0.263	0.449	−0.186	2.231	0.026	Significant
Education	Non-Bachelor vs. Bachelor+	EE→BI	−0.029	0.093	−0.122	2.219	0.027	Significant
Education	Non-Bachelor vs. Bachelor+	HT→BI	0.018	−0.186	0.203	3.454	0.001	Significant
Education	Non-Bachelor vs. Bachelor+	PC→BI	0.196	0.388	−0.193	3.308	0.001	Significant
Expenditure	<IDR 2.5M vs IDR 2.5–5M	EE→BI	−0.032	0.108	−0.140	2.287	0.022	Significant
Expenditure	IDR 2.5–5M vs ≥IDR 5M	HM→BI	0.186	−0.018	0.204	2.475	0.013	Significant
Expenditure	IDR 2.5–5M vs ≥IDR 5M	PEV→BI	0.013	0.199	−0.187	2.276	0.023	Significant
Experience	Beginner ≤3yrs vs Intermediate 3–5yrs	PE→BI	0.033	0.276	−0.243	2.892	0.004	Significant
Experience	Beginner ≤3yrs vs Intermediate 3–5yrs	HT→BI	0.180	−0.189	0.369	4.066	<0.001	Significant
Experience	Beginner ≤3yrs vs Intermediate 3–5yrs	IC→BI	0.369	0.149	0.220	2.554	0.011	Significant
Experience	Beginner ≤3yrs vs Intermediate 3–5yrs	PEV→BI	0.272	−0.041	0.313	3.483	0.001	Significant
Experience	Beginner ≤3yrs vs Intermediate 3–5yrs	PC→BI	−0.027	0.315	−0.343	3.413	0.001	Significant
Distance	All Comparison	—	—	—	—	—	>0.05	Not Significant

4.4. CART Decision Rules and the Policy Credibility Gatekeeper Effect

Evaluated via 5-fold stratified cross-validation, the CART algorithm achieved an overall classification accuracy of 61.45% (F1-score = 0.6023) across the five highly imbalanced Rogers adopter categories. While an overall accuracy of 61.45% might appear modest in binary deterministic systems, it represents a highly robust performance in the context of multi-class human behavioral intention modeling. Predicting the placement of individuals into Rogers' five highly imbalanced adopter categories is inherently limited by socio-economic noise and latent cognitive biases. The achieved F1-score of 0.6023 substantially outperforms the baseline random probability classifier for a five-class imbalanced dataset. More importantly, within this hybrid architecture, CART is not deployed as a standalone predictive black-box, but as an inferential tool for rule extraction. The primary objective is identifying the Gini-impurity reduction thresholds that signal non-compensatory bounds a task for which the algorithm's performance is both theoretically appropriate and empirically sufficient.

The decision tree selected Policy Credibility (PC) as the root node, the single variable that, when split, produces the greatest reduction in classification impurity across the entire sample. The primary decision rule extracted is as follows:

IF PC ≤ -0.46:Agent = Laggard (unconditionally, regardless of all other constructs)

IF PC > -0.46 AND IC > 0.67 AND (PC × IC) > 0.82:Agent = Early Adopter

The stability of the extracted decision rules, including the PC ≤ −0.46 threshold, was secured through 5-Fold Stratified Cross-Validation. This technique ensured the model was cross-evaluated across five different data folds while maintaining the representative proportion of adopter classes.

This result is the empirical core of the Gatekeeper Effect. Once a respondent's Policy Credibility index falls at or below −0.46, the algorithm classifies that respondent as a Laggard irrespective of their scores on Performance Expectancy, Hedonic Motivation, Perceived Economic Value, or any other construct in the model. No combination of technical superiority or economic incentive alters this classification. This is the defining signature of non-compensatory decision-making: distrust does not merely reduce the weight of other attributes; it removes them from consideration entirely. A structural model reporting β = 0.297 for PC communicates that policy credibility matters on average; it cannot communicate that below a specific threshold, policy credibility is the only variable that matters. This distinction directly substantiates the methodological rationale advanced in Section 2.5.1 for combining PLS-SEM with CART rather than treating either method as sufficient in isolation.

The structural topology of these non-compensatory thresholds is visualized in the extracted decision tree (Figure 3). To provide actionable behavioral interpretations, the dominant decision rules mapping policy credibility interactions to terminal adopter categories are formalized in Table 6.

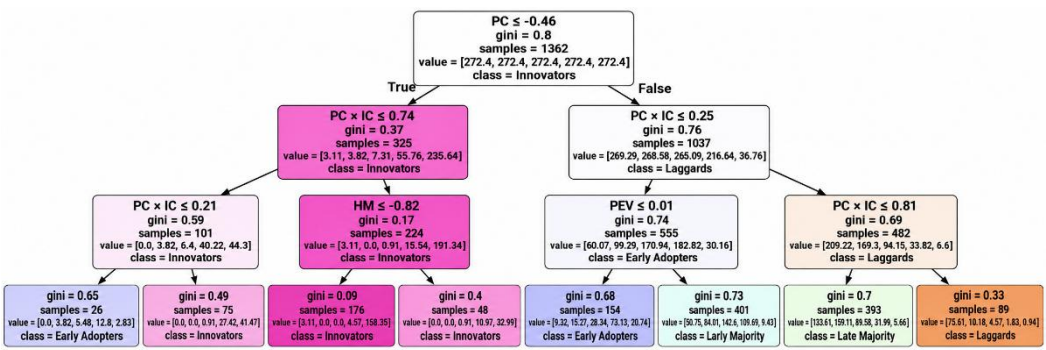

Fig. 3. CART decision tree extracting non-compensatory behavioral rules based on Policy Credibility (PC)

Table 6. Dominant Non-Compensatory Decision Rules Extracted via CART

Rule	Split Conditions (Thresholds)	Terminal Classification	Behavioral Interpretation
Rule 1	IF Policy Credibility (PC) ≤ -0.46	→ Laggards / Late Majority	The Gatekeeper Effect: Unconditional barrier to early adoption. Distrust in policy longevity locks consumers into late-market segments, negating any subsequent infrastructure (IC) or hedonic (HM) advantages.
Rule 2	IF PC > -0.46 AND (PC × IC) ≤ 0.25AND PEV > 0.01	→ Early Majority	Economic Dependency: When basic institutional trust is met but policy-infrastructure synergy is low, mainstream adoption becomes heavily reliant on Perceived Economic Value (PEV).
Rule 3	IF PC > -0.46 AND (PC × IC) > 0.81	→ Innovators	The Synergistic Catalyst: High concurrent trust in both policy continuity and charging infrastructure unlocks immediate, early-market entry without requiring economic compensations.

As Table 6 demonstrates, distrust in policy longevity acts as an absolute barrier, negating any subsequent infrastructure presence. This gatekeeper logic forms the behavioral foundation for the simulation phase.

4.5. Agent-Based Simulation and Genetic Algorithm Optimization

4.5.1. Baseline Diffusion Dynamics and the Chasm Constraint

The calibrated ABM incorporating household electrical capacity constraints (48.3% of the sample at ≤900VA), the intention-to-behavior gap, and a five-year vehicle replacement cycle was run over a 120-month (10-year) simulation horizon under a range of policy scenarios.

Under the Business-As-Usual (BAU) scenario, reflecting current levels of policy credibility and existing SPKLU density, cumulative adoption reaches only 10.94% after ten years. Notably, even under an optimistic scenario combining an elevated Policy Credibility index (PC = 2.0) with substantially expanded infrastructure (40 SPKLU units), adoption stagnates at 11.99%, a gain of barely one percentage point despite a considerable increase in both policy trust and physical infrastructure. Both scenarios remain trapped below what diffusion theory identifies as "the Chasm," the approximately 16% adoption threshold separating early-market adopters (Innovators and Early Adopters) from mainstream market uptake (Majority segments), following Moore's *Crossing the Chasm* framework applied to green technology diffusion (Moore, 2014).

This result carries a critical implication: within the current range of policy credibility improvement and infrastructure expansion tested, the model cannot break out of early-market adoption. The binding constraints on mainstream crossing are not policy credibility or SPKLU density in isolation, but structural factors external to both specifically, household electrical capacity limitations and battery range anxiety, which are examined below.

4.5.2. Breaking the Chasm: Technological and Fiscal Thresholds

Genetic Algorithm optimization via BehaviorSearch was used to identify the parameter combination required to cross the 50% majority adoption tipping point. Results indicate that crossing the Chasm and approaching majority-level adoption is achievable only through the joint presence of two conditions absent from the BAU and moderate-optimism scenarios above: a battery range breakthrough to approximately 130 km per charge, and an increased purchase subsidy of approximately IDR 9 million. Neither policy credibility improvement, nor infrastructure expansion alone nor their combination, as shown in Section 3.4.1, is sufficient to reach majority adoption without this technological and fiscal threshold being met concurrently. This indicates that the adoption ceiling in this corridor is presently bounded jointly by institutional trust *and* by product-level range performance, and that policy credibility, while necessary, is not alone sufficient for mainstream crossing.

4.5.3. The Resource-Efficient Leverage Point and Diminishing Returns

Within the joint search space of Policy Credibility (0–3) and SPKLU unit count (5–50), the Genetic Algorithm identified a global optimum of 55.34% adoption, achieved at PC = 2.45, 46 SPKLU units, an IDR 9 million subsidy, and 130 km battery range.

However, the optimization also identified a resource-efficient leverage point at a substantially lower infrastructure count: 31 SPKLU units, holding other optimized parameters constant, already achieves 53.35% adoption within 1.99 percentage points of the global optimum. Expanding infrastructure beyond this point, from 31 to 46 units (a 48% increase in physical SPKLU count), buys only this residual 1.99-point gain. This plateau indicates a clear spatial infrastructure saturation point, representing diminishing marginal returns: once charging accessibility crosses a sufficient density threshold for the corridor's commuting geography, additional stations serve overlapping catchment areas rather than unlocking new adopter segments.

To address simulation uncertainty and spatial stochasticity, the Genetic Algorithm evaluation process was strictly constrained. Each of the 205 candidate scenario combinations was evaluated across 3 independent stochastic replications, accumulating to 615 total model executions. Fitness was scored based on the mean adoption rate across these replications. Furthermore, sensitivity analysis via BehaviorSpace demonstrated that decentralizing infrastructure to the 30-unit saturation point effectively acts as a spatial uncertainty reducer, dropping the standard deviation across replications from 0.68% down to the 0.11%–0.30% range.

This finding directly parallels, and empirically substantiates, the methodological framing established in Section 2.5.1: just as Policy Credibility acts as a non-compensatory behavioral gatekeeper at the individual level (Section 3.3), infrastructure density exhibits a saturating, non-linear return profile at the systems level. Beyond 31 units, capital allocated to additional SPKLU construction in this corridor generates negligible marginal adoption benefit and represents, in fiscal terms, an inefficient use of constrained public or donor-backed capital. The comparative impact of these variables from the Business-As-Usual stagnation to the successful crossing of the market majority tipping point under optimal conditions is tracked across the 120-month simulated diffusion trajectories illustrated in Figure 4.

5. Discussion

5.1. Methodological Transparency: Cognitive Overlap in Early-Stage Technology Evaluation

The measurement model reported in Section 3.1 achieved acceptable convergent validity and reliability across all constructs, but discriminant validity assessment via the Heterotrait-Monotrait ratio (HTMT) revealed two construct pairs exceeding the conventional 0.9 threshold: Habit and Effort Expectancy (HT-EE), and Hedonic Motivation and Communal Identity and Norms (HM-CIN). The HTMT violation reported in Section 3.1 is, by the conventional criteria this study applies, a discriminant validity limitation rather than a fully resolved measurement outcome, and we do not present it as such. We report a plausible substantive explanation for why this overlap occurred rather than attributing it to random measurement error while explicitly acknowledging that this explanation is post-hoc and that it does not substitute for formal model respecification. We recommend this respecification as a necessary step for future confirmatory work (Section 5.5), and we note that both affected first-order constructs (HT, EE) were independently found non-significant in the structural model (Section 3.1), reducing, but not eliminating, the risk that this validity limitation drives a substantive conclusion in the present study.

Table 7. Genetic Algorithm optimization and simulated scenario configurations

Configuration	PC Index	SPKLU Units	Subsidy	Battery Range	Adoption Rate
Business-As-Usual	0	Current baseline	Current	Current	10.94%
Optimistic (non-breakthrough)	2.0	40	Current	Current	11.99%
Resource-Efficient Leverage Point	2.45	31	IDR 9M	130 km	53.35%
Global Optimum	2.45	46	IDR 9M	130 km	55.34%

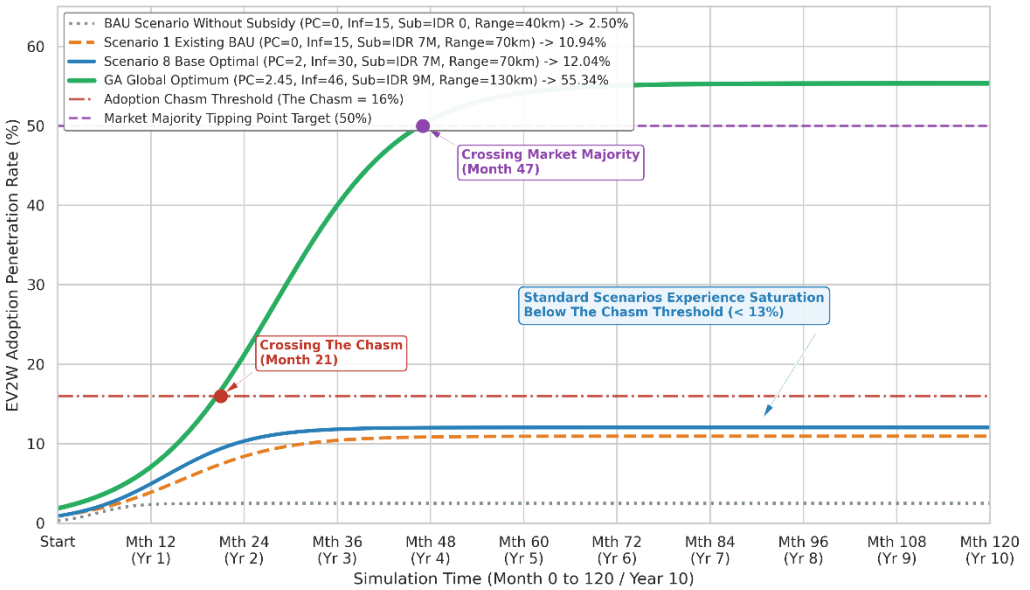

Fig. 4. Simulated 10-year S-Curve diffusion trajectory across baseline and optimized policy scenarios

Respondents in this sample had never used an EV2W. Their only available reference point for evaluating "ease of use" is the conventional gasoline motorcycle they currently ride. Under these conditions, Effort Expectancy, which is a forward-looking judgment about a new technology, cognitively collapses into Habit, a backward-looking judgment about an existing one, because respondents lack the experiential basis to separate the two. They are not answering "how easy will this new machine be to use," but rather "how does this compare to what I already know how to use," which is functionally the Habit question. An identical mechanism plausibly explains the HM-CIN overlap: without lived experience of EV2W ownership, the anticipated enjoyment of riding one (Hedonic Motivation) is not yet psychologically distinct from the anticipated social approval of being seen riding one (Communal Identity and Norms), because neither judgment is anchored in direct experience and both instead draw on the same undifferentiated mental model of "what my neighbors would think of this new machine."

This interpretation is consistent with anchoring theory in early-stage technology evaluation, where consumers process unfamiliar products by mapping them onto pre-existing reference categories rather than evaluating them on independent attribute dimensions (Mariscal et al., 2026). It also explains why this overlap did not appear in the pilot test to the point where intervention was required beyond the single PEV4 rewording (Section 2.3): the pilot sample, like the full sample, is entirely made up of non-adopters, so the anchoring mechanism operates uniformly across both stages rather than as sampling noise specific to one wave of data collection.

This finding directly motivates the second stage of our hybrid design. If Effort Expectancy and Habit are not yet fully differentiated in respondent cognition, then a linear structural path coefficient estimated separately for each construct is estimating two partially overlapping signals as though they were independent, which plausibly contributes to the non-significance of both HT and EE in the pooled structural model (Section 3.1). CART does not require this separation to be resolved a priori: it partitions respondents directly on latent score values regardless of which underlying construct that score maps theoretically to and remains diagnostically informative even where two upstream constructs are cognitively entangled. This is a second, independent justification alongside the non-compensatory threshold argument in Section 2.5.1 for why this study did not rely on PLS-SEM in isolation. Where construct differentiation is incomplete, machine-

learning-based partitioning offers a more robust description of actual decision structure than a structural coefficient can.

5.2. The Political Economy of the Gatekeeper Effect

The CART-identified threshold PC ≤ −0.46 as an unconditional disqualifying condition is not merely a statistical artifact of this sample. It is consistent with a broader institutional-economics argument that a subsidy for a multi-year durable asset functions as an implicit long-term contract between state and consumer, and that consumers price that contract based on their assessment of its enforceability. An EV2W purchase commits the buyer to a 5–7 year asset horizon; a subsidy program with annual eligibility revision, opaque disbursement timing, and abrupt suspension gives the buyer no comparable multi-year assurance on the other side of that contract. Under these conditions, rational discounting of subsidy value is not a market failure that requires behavioral correction; rather, it is the appropriate response to an institution that has not demonstrated durability.

This framing clarifies why Indonesia's current subsidy structure for two-wheeled electric vehicles (EV2W) creates the type of institutional vulnerability identified by the "Gatekeeper Effect." The subsidy is instantiated through ministerial regulation subject to annual revision, not through statute. Disbursement criteria have changed within single budget cycles. The program has been suspended without extended notice. Each of these features is a rational signal to a forward-looking consumer that the program's horizon is uncertain, and the CART threshold indicates that a substantial share of the suburban commuter population has already priced in that uncertainty to the point of behavioral disqualification a point beyond which no improvement in vehicle economics or performance changes the purchase decision.

Comparative regional evidence supports the claim that credibility, not subsidy magnitude, is the operative variable. India's transition from the original FAME II demand-incentive structure to the Production-Linked Incentive (PLI) scheme replaced an annually renewable subsidy pool with a multi-year supply-chain roadmap, providing manufacturers and consumers alike with a longer institutional horizon against which to plan (Dhairiyasamy et al., 2024; Ghosh & Sarkar, 2026). Thailand's EV30@30 program took a structurally different approach: incentives were anchored in the Revenue Code rather than issued through annual ministerial regulation, rendering them statutorily difficult to reverse without a legislative act rather than an administrative decision(Chonsalasin et al., 2024a; Prabpayak et al., 2025). Neither case demonstrates that India or Thailand offered larger subsidies than Indonesia's IDR 7 million per-unit incentive; both demonstrate that the *institutional form* of the commitment statutory versus administrative, multi-year versus annual is the variable that differentiates sustained market response from the stagnation observed in this study's setting. This is consistent with the PC × PEV moderation result in Section 3.1: economic value only converts into behavioral intention where policy trust is present to validate it, and no amount of increasing the economic value term appears capable of compensating for a credibility deficit once that deficit crosses the CART-identified threshold.

Vietnam offers a third institutional pathway worth noting for contrast: VinFast's vertically integrated, state-linked commercial position allowed a private actor to substitute a durable *commercial* signal (guaranteed service infrastructure, resale value support, manufacturer continuity) for the *institutional* signal that Indonesia's policy architecture has so far failed to provide (Ngo et al., 2022; Nguyen & Earl, 2025). This suggests that credible commitment can originate from either state- or firm-level institutional structures, but that some source of durable commitment, public or private, appears necessary to clear the threshold this study identifies.

The validation of the Policy Credibility construct as a non-compensatory gatekeeper fundamentally challenges the prevailing consensus in EV transition literature, which largely treats policy instruments as additive. Our findings suggest that in emerging markets with a history of regulatory hysteresis, subsidies do not function as independent economic levers; they are conditional contracts. When the state relies on administrative regulations subject to annual adjustments rather than statutory, multi-year legislative anchoring, the perceived risk of program discontinuation overwhelms the economic incentive. Consequently, the threshold identified (PC ≤ −0.46) mathematically captures the exact point where

structural distrust nullifies technological and fiscal advantages.

5.3. Infrastructure Saturation and the Sequencing of Catalytic Capital

The Genetic Algorithm result reported in Section 3.4.3 a 1.99 percentage-point adoption gain from a 48% increase in SPKLU count beyond the 31-unit leverage point has a direct fiscal reading: within this corridor, capital allocated to charging infrastructure beyond approximately 30–31 units is not idle, but it is inefficient, purchasing a small residual gain at a cost disproportionate to that gain relative to the first 31 units. This is a spatial saturation effect consistent with declining marginal utility of network density once catchment areas for existing nodes begin to overlap along the corridor's actual commuting geometry.

From a transportation planning perspective, the identification of a 31-unit spatial saturation threshold in a dual-regency suburban corridor highlights a critical inefficiency in current network expansion models. When evaluated against global metrics, 31 units across the Sleman-Bantul area constitutes a relatively sparse node-per-square-kilometer density compared to the aggressive deployment seen in mature EV hubs like Shenzhen or Oslo. However, the simulation proves that within emerging suburban topologies characterized by fixed point-to-point commuting rather than randomized urban grid mobility, infrastructure requirements are dictated by nodal interception along primary arterial corridors, not by uniform geographic density. Consequently, capital expenditure that aims to increase the raw density metric beyond this 31-unit threshold effectively funds spatial redundancy. For policymakers, this confirms that suburban EV2W transition does not require mirroring the capital-intensive charging densities of megacities; it requires targeted interception at high-dwell-time commuting nodes, tightly coupled with the resolution of legislative credibility.

Consequently, these results have direct policy implications for the structuring of internationally financed green-transition capital, specifically the Just Energy Transition Partnership (JETP), through which Indonesia has received catalytic and concessional financing commitments explicitly framed around accelerating the country's energy and transport transition(Hersaputri et al., 2024; Wardhana et al., 2024). JETP capital, like domestic subsidy capital, is typically directed toward physical asset deployment charging infrastructure, grid upgrades, and generation capacity because physical assets are legible, measurable, and politically demonstrable in a way that "improved regulatory credibility" is not. This study's results indicate that this allocation logic, applied to a market segment still below the $PC \leq -0.46$ gatekeeper threshold, risks financing infrastructure that a distrustful population will simply decline to use, regardless of its physical availability. The result is not merely underutilized capital it is *spatial redundancy*: a built asset base exceeding the functional catchment requirement of the addressable market, financed under the assumption that infrastructure scarcity, rather than institutional distrust, was the binding constraint on adoption.

The sequencing implication is direct. Where a population sits below the Gatekeeper threshold identified in Section 3.3, catalytic capital directed at infrastructure expansion should be treated as premature relative to capital directed at establishing the statutory, multi-year policy anchoring discussed in Section 4.2. This does not imply that infrastructure investment is unnecessary; the 31-unit leverage point demonstrates that a baseline infrastructure floor is a precondition for the 53.35% adoption ceiling identified in this study. It implies that infrastructure investment beyond that floor, absent a corresponding resolution of the institutional credibility deficit, does not purchase proportional adoption gains, and that donor and domestic capital allocated on the assumption that it does is being spent against the wrong constraint.

6. Conclusion and Policy Implications

This study set out to determine why aggressive subsidy expenditure and infrastructure expansion have failed to move Indonesian EV2W adoption beyond 2% of total motorcycle sales. The answer is not that subsidies are too small or that charging stations are too few. It is that both instruments are being deployed against the wrong constraint. Adoption in the Sleman-Bantul corridor is governed first by a binary institutional trust threshold, and only second by economic and infrastructural variables that current policy treats as primary. The four policy implications below follow directly from that finding.

6.1. Credibility Before Expenditure

Based on our cross-sectional modeling, a Policy Credibility index at or below −0.46 strongly binds consumers to late-adopter categories, significantly dampening the effectiveness of subsequent subsidy or infrastructure interventions. Within the boundaries of our suburban sample, this indicates that fiscal allocation made before addressing this institutional trust deficit risks substantial inefficiency.

Therefore, we suggest that infrastructure capital expenditure should ideally be aligned with, rather than precede, the establishment of credible policy signals. Moving Indonesia's EV2W subsidy from an annually revised administrative instrument to a multi-year statutory roadmap could help mitigate the discounting effect observed in our analysis.

6.2. The Infrastructure Leverage Point

Charging infrastructure beyond approximately 30–31 SPKLU units in a corridor of this size and commuting geometry does not sit idle, but it returns adoption gains disproportionately small relative to its cost. The jump from 31 to 46 units a 48% increase in station count purchases only adds 1.99 additional percentage points of adoption. This is spatial redundancy, not infrastructure failure: stations built beyond this density serve overlapping catchment areas rather than reaching new adopters.

For suburban corridors comparable to Sleman-Bantul, the prescriptive target is 30 units, not the maximal density that available capital could otherwise fund. Placement should prioritize high-dwell-time mobility hubs, commuter rail interchanges, university campuses, and commercial centers over even distribution along arterial roads, since dwell-time locations serve the dual-node home-work evaluation pattern identified in the ABM more efficiently than route-based placement. Battery-swapping stations (SPBKLU) should be integrated into this fixed footprint to multiply functional coverage without adding station count. This directly addresses the 48.3% of the population operating on ≤900VA household connections, who cannot rely on home charging as a primary solution.

6.3. Segment-Specific Communication

The Multi-Group Analysis results indicate that a single national messaging strategy is measurably inefficient. Perceived Economic Value is a strong predictor for male commuters ($\beta = 0.235$) and statistically irrelevant for female commuters ($\beta = -0.051$); Policy Credibility carries outsized weight for commuters aged 40 and above ($\beta = 0.449$) relative to the sample average ($\beta = 0.297$); Habit operates as a significant barrier only among riders with more than five years of riding experience.

Communication strategy should be segmented accordingly. Younger, male commuters respond to total-cost-of-ownership and fuel-savings framing economic arguments that this study confirms are effective for this segment specifically, not universally. Older and more experienced riders require a different message entirely: regulatory assurance, program permanence, and evidence of statutory backing, since this segment is both most exposed to habit-based resistance and most sensitive to the credibility signal identified in Section 4.2. Treating these as a single undifferentiated target audience wastes communication budget on arguments that a substantial share of the population will not act on.

6.4. Overcoming the Chasm: The Battery Range Threshold

No combination of policy credibility improvement and infrastructure expansion tested in this study moves adoption past 11.99%, below Moore's Chasm threshold of 16% separating early-market from mainstream adoption. Majority-level adoption (53.35%–55.34%) becomes reachable only when battery range crosses approximately 130 km per charge in combination with a subsidy near IDR 9 million. Institutional trust and infrastructure density are necessary conditions for adoption; they are not sufficient ones. Suburban commuters in this corridor carry legitimate range anxiety at current battery specifications, and no regulatory or fiscal instrument substitutes for the underlying product limitation. Policy attention directed exclusively at subsidy value and charging density, without parallel pressure on domestic battery R&D and manufacturing standards, will not clear this threshold regardless of how well Sections 5.1 through 5.3 are implemented.

6.5. Limitations and Future Research

Three limitations bound the claims made in this study and should guide their application.

First, the empirical and simulated population is drawn exclusively from the Sleman-Bantul

suburban commuter archetype: moderate-density, 10–25 km daily commutes, strong communal social structure. The 31-unit infrastructure threshold and the specific PC ≤ −0.46 gatekeeper value are calibrated to this geography and commuting pattern; neither figure should be applied to megacity contexts such as Jakarta without re-estimation, since commute distance distribution, existing infrastructure density, and social network structure differ materially (Bayham et al., 2022; Ryu et al., 2026).

Second, projecting a 10-year diffusion trajectory (120 simulation ticks) using cross-sectional survey data carries inherent epistemological assumptions. The model assumes that the underlying behavioral rules, risk tolerances, and technological perceptions captured in the initial survey snapshot remain structurally static over the decade. Consequently, the ABM output should not be interpreted as a deterministic forecast of actual future sales volumes. Rather, it serves as an exploratory "what-if" laboratory that isolates the structural limits of current adoption dynamics, demonstrating exactly how far the existing cognitive barriers will constrain diffusion if public attitudes and institutional trust do not organically evolve. Future work should incorporate reinforcement-learning agents capable of updating their trust parameters endogenously over the simulation window.

Third, the discriminant validity limitation discussed in Section 4.1, HTMT values exceeding 0.9 for HT-EE and HM-CIN, indicates that the present first-order construct specification does not fully separate constructs that suburban commuters have not yet learned to distinguish cognitively in the absence of direct EV2W experience. Future PLS-SEM applications in pre-adoption technology contexts should specify Habit, Effort Expectancy, Hedonic Motivation, and Communal Identity and Norms as Higher-Order Constructs (HOC), allowing shared variance to be modeled explicitly rather than treated as a validity threshold to be cleared or reported as a caveat. Beyond these three limitations, commercial fleet operators, ride-hailing, and logistics were excluded from this sample and follow a different economic logic driven by daily utilization rates rather than personal commute convenience. Extending this hybrid framework to fleet operators represents a distinct research agenda with its own credibility and infrastructure thresholds likely to differ from those reported here.

Fourth, this sequential hybrid framework inherently carries the risk of error propagation. Because the deterministic CART rules are constructed using the Latent Variable Scores extracted from the PLS-SEM model, the classification quality is fully dependent on the measurement quality of the first stage. Consequently, any unmitigated empirical overlap between constructs in the PLS-SEM phase can influence the interpretation of the decision rules extracted by CART, which in turn dictates the macroscopic diffusion trajectories in the ABM. Future modeling efforts should consider probabilistic decision boundaries to better absorb and mitigate propagated uncertainty across methodological stages.

The central claim of this study is narrow and falsifiable: institutional trust functions as a gate, not a gradient. Below a measurable threshold, consumers do not partially discount a subsidy; they exclude it from consideration entirely. Governments that continue to fund charging infrastructure and price incentives while leaving that gate closed are not failing to spend enough. They are spending against the wrong variable.

Finally, the data collection strategy, which incorporated social media recruitment and voluntary participation, inherently introduces potential self-selection bias. Individuals who opt into technology-related surveys may systematically differ from the general population, potentially overrepresenting technologically interested commuters. While this bias might inflate the baseline proportion of early-market segments, it does not invalidate the study's primary theoretical contribution. The identification of the Gatekeeper Effect (PC ≤ −0.46) demonstrates a structural behavioral bound that operates regardless of the sample's initial technology enthusiasm, though future probability-sampled research is recommended to calibrate these parameters across broader demographics.

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