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Prediction of Battery Electric Vehicle (BEV) Adoption in Indonesia Using Agent-Based Modelling and Simulation: An Integrated Model Implementation

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ABSTRACT: The Indonesian government has implemented policies to promote Electric Vehicle (EV) adoption to reduce carbon emissions. However, challenges like insufficient infrastructure, reliability concerns, and high costs hinder personal EV adoption. This study integrates behavioral theories (TPB, TAM, UTAUT) into Agent-Based Modeling (ABM) to simulate Battery Electric Vehicle (BEV) adoption in Indonesia.The research aims to understand TPB's applicability in ABM simulations for BEV adoption dynamics and emphasizes the importance of model calibration. It provides insights for decision-makers, highlighting ABM as a tool for shaping regulations during green transitions. Findings suggest that increasing supporting infrastructure, manufacturers' support, and promotional policies could significantly boost BEV adoption, with government regulations having the most positive impact. The study also noted a discrepancy between simulated and empirical sales during the COVID-19 pandemic, indicating that global events can negatively affect domestic green transitions.

KEYWORDS - Green transition, electric vehicle, agent-based modelling, technology adoption

I. INTRODUCTION

Indonesia, one of the largest developing countries globally, is projected to have a population of 300 million by 2030 [1]. This growth has been accompanied by a proportional increase in carbon emissions from the transportation sector. As vehicular traffic surges due to urbanization and economic growth, the environmental ramifications become increasingly pronounced. As of the latest official data from 2019, the transportation sector is the second-largest CO2 emitter (24.64%) after the energy production sector (47.81%), equating to 127,881 Gg CO2e. This number has been increasing by an average of 7.17% each year from 2010 to 2019 [2]. This phenomenon not only threatens environmental sustainability but also poses significant repercussions on public health. The escalating levels of air pollution contribute to respiratory diseases and other health complications, especially for those who live in highly urbanized areas such as Jakarta [3].

There is a pressing need to transition towards greener transportation alternatives. One promising solution lies in the electrification of transportation through the mass adoption of electric vehicles (EVs). Several studies have shown that EVs offer a sustainable alternative to internal combustion engine vehicles (ICEVs) and may decrease air pollution in urban areas [4, 5, 6, 7]. The Indonesian government has been promoting this transition through President Regulation Number 55 of 2019 on the Program for Acceleration of Battery Electric Vehicle (BEV) for Road Transportation. This regulation laid the groundwork for various incentives for potential BEV users, the development of domestic BEV manufacturing, and the creation of supporting BEV infrastructure. It is further strengthened by the Indonesian Government's pledge to reduce emissions by 29% unconditionally and up to 41% with foreign aid compared to the 2030 business-as-usual scenario [8]. Besides alleviating environmental impacts, these policies and the widespread implementation of EVs might bolster the development of a local industry centered around BEV production. In 2020, Indonesia contributed 37% of global nickel production, making it the largest nickel producer worldwide [9]. Nickel is a crucial material in lithium-ion battery cathodes used by most current BEVs [10]. Reducing the need for fossil fuels could also enhance Indonesia's energy independence, given that the country was a net oil importer in 2021 [11].

Advances in electric vehicle (EV) technology have made widespread electrification of transport vehicles in developing countries more economically viable. Looking ahead, the use of EVs will likely increase due to factors such as the instability of petroleum supply and stricter environmental regulations globally. While EV sales in Indonesia have been growing since 2019, their sustainability remains uncertain [12]. There are still many barriers to EV adoption, such as higher costs, lack of supporting infrastructure, and perceived inferior overall performance compared to ICEVs [13, 14, 15]. However, there are also promoting factors, such as supportive regulations, social influence, and environmental consciousness [14, 15, 16].

To understand the drivers behind interest in product usage, numerous theories have been put forth. Among these, the Theory of Planned Behavior (TPB) and its variations stand out as some of the most widely recognized frameworks, addressing attitudes, subjective norms, and perceived behavioral control [17]. Many theories have also expanded upon TPB to better understand factors that can predict behavior in technology adoption, such as the Technology Acceptance Model (TAM), which presumes a mediating role of perceived ease of use and perceived usefulness in the relationship between system characteristics and system use [18]. Another influential theory is The Unified Theory of Acceptance and Use of Technology (UTAUT), which predicts technology acceptance by examining the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions [19]. The UTAUT2 model, an extension of UTAUT, is used to study acceptance and use of technology in a consumer context, incorporating additional constructs such as hedonic motivation, price value, and habit, with individual differences hypothesized to moderate the effects of these constructs on behavioral intention and technology use [20]. Another concept that could add to capturing the complexity of new technology adoption is perceived risk, which in some studies has been used together with TPB [15, 21, 22, 23]. These theories are typically classified as variance theory, where the precursor (independent variable) serves as both a necessary and sufficient condition to explain the outcome (dependent variable). Variance theory focuses on variables and assumes that their time ordering is not significant [24].

Theoretical models often lack a visual representation of how technology adoption works in real-world scenarios. This is where Agent-Based Modeling (ABM) comes into play. One of the earliest studies using ABM for BEV usage diffusion was conducted by a past study [25]. This study developed an agent-based model to simulate the introduction of four policy scenarios aimed at promoting EV adoption within an urban community, benchmarked against a baseline scenario. The evaluated policy scenarios included reducing vehicle purchase costs through subsidies, expanding the local public charging infrastructure, increasing the number and visibility of BEVs on roads via government fleet acquisitions, and a hybrid approach combining these three strategies. The results indicated the effectiveness of policy options that enhance awareness and familiarity with BEV technology, with the hybrid policy proving most successful in encouraging BEV adoption by increasing the visibility and ubiquity of BEV technology within the community.

In the context of Indonesia, a study [25] employed ABM to simulate the diffusion of Natural Gas Vehicles (NGVs). This study examined the sluggish adoption of NGVs despite government efforts to develop supporting infrastructure and regulations. The research aimed to elucidate the consumer adoption decision-making process and identify potential policy interventions to stimulate NGV adoption. Two models were compared: a non-psychological model and a psychological model incorporating cognitive factors. Through ABM, the psychological model demonstrated superior explanatory power regarding the underlying mechanisms driving adoption decisions.

However, these models often incorporate complex external factors, necessitating extensive calibration and straining resources. Empirical data limitations for intricate factors can yield unreliable outcomes. Interpretability challenges arise as stakeholders may struggle to comprehend highly complex models, and substantial computational burdens can impede practical application. Furthermore, the risk of overfitting increases with excessive external factors, compromising generalizability. While real-world phenomena involve trade-offs, researchers must judiciously prioritize relevant factors. Consequently, simplicity grounded in robust data often leads to more effective ABMs, balancing realism, and feasibility [27, 28].

This paper aims to address the gap by developing a simpler integrated framework based on the combination of TPB, TAM, and UTAUT within an ABM framework to simulate BEV adoption dynamics in Indonesia. The adoption model employed will primarily refer to the one developed in [15]. Although the previously proposed model offers valuable insights, it lacks the ability to capture the dynamic nature of technology adoption. To enhance the prediction capability, this study incorporates temporal dimensions, exploring how adoption evolves over time. Furthermore, by integrating process theory, which considers precursors and outcomes in sequence and embraces probabilistic rearrangement rather than strict causality [24], this paper diverges from the traditional variance theory approach.

By simulating the interplay between individual-level factors and external influences, this study seeks to provide insights into the temporal evolution of EV adoption and inform evidence-based strategies for promoting sustainable transportation in Indonesia. Through this interdisciplinary approach, we aim to contribute to the growing body of literature on technology adoption and sustainable development.

II. LITERATURE REVIEW

2.1 Alternative Fuel and Electric Vehicle Adoption in Indonesia

Indonesia's efforts to curb carbon emissions in the car market began with the promotion of high-efficiency ICEVs, which also included alternatives to petroleum, such as natural gas or biofuels, as per the Minister of Industry Decree No. 33/2013. The widespread adoption of BEVs took off at the beginning of 2020, following the enactment of President Regulation Number 55 of 2019. That year, only a few manufacturers, namely Hyundai, Toyota, and Lexus, introduced their BEV models to the Indonesian market, according to GAIKINDO's 2021 report, which is the Association of Indonesia Automotive Industries that represents producers, distributors, and manufacturers of automotive products in Indonesia. Over the subsequent years, an increasing number of brands from Japan, China, and Germany have been bringing their BEVs to the market. Additionally, Hybrid Electric Vehicles (HEVs) are also available, and GAIKINDO's annual wholesale data indicates that HEVs enjoy greater popularity than BEVs, as evidenced in Table 1.

Table 1. GAIKINDO Annual Vehicle Wholesale Data in Indonesia, 2018-2024

Year	2018	2019	2020	2021	2022	2023
Total BEV Sales (units)	0	0	125	687	10,327	17,062
Total HEV Sales (units)	672	705	1,110	2,506	10,344	50,617
Total wholesales (units)	151,308	1,030,126	532,027	887,202	1,048,040	1,005,802
HEV+BEV Marketshare	0.06%	0.07%	0.23%	0.36%	1.97%	6.73%
BEV Marketshare	0.00%	0.00%	0.02%	0.08%	0.99%	1.70%
HEV Marketshare	0.06%	0.07%	0.21%	0.28%	0.99%	5.03%
BEV Typemodel count	0	0	7	10	17	39
HEV Typemodel count	8	12	12	10	19	42

The present study employs wholesale data commencing from 2018, marking the inaugural year in which HEV sales were documented by GAIKINDO. Conversely, BEV sales data were incorporated starting from 2020. It is noteworthy that both HEVs and BEVs were available in the Indonesian market prior to these dates; however, their sales were facilitated exclusively through specialized automobile importers and, as such, are not reflected in this dataset.

This study concentrates on the adoption of BEV cars in Indonesia for two primary reasons. Firstly, although HEVs currently dominate the market, the Indonesian government is steering efforts towards BEVs, anticipating a boost to the nation's nickel industry. Secondly, the availability of detailed car wholesale data facilitates this focus, unlike data for motorcycles or the total motorized vehicle population, which lacks differentiation between ICEVs and EVs.

The cited study [15] provides a thorough analysis of the factors affecting Indonesia's adoption of BEVs. By using an integrative methodology, the authors created a model that combines the TPB, the UTAUT2, and the idea of perceived risk in order to clarify the variables influencing consumers' intentions toward the use of electric vehicles (EVs) in the Indonesian setting. Perceived risk is said to have a negative impact on four important UTAUT2 constructs: performance expectancy, effort expectancy, social influence, and enabling conditions. Moreover, it implies that these constructs, in addition to attitude, subjective norm, and perceived behavioral control—all essential components of TPB—co-influence the inclination to purchase electric vehicles. Using data from a sample of 526 Indonesians, the study uses structural equation modeling to validate the model. The study validates the model through structural equation modeling, utilizing data from a sample of 526 Indonesian respondents who have expressed interest in EVs. Results indicate that perceived risk, performance expectancy, effort expectancy, social influence, facilitating conditions, attitude, and subjective norm significantly influence the intention to utilize EVs, while perceived behavioral control does not demonstrate a significant effect. Fig.1 shows the adoption model developed from the study.

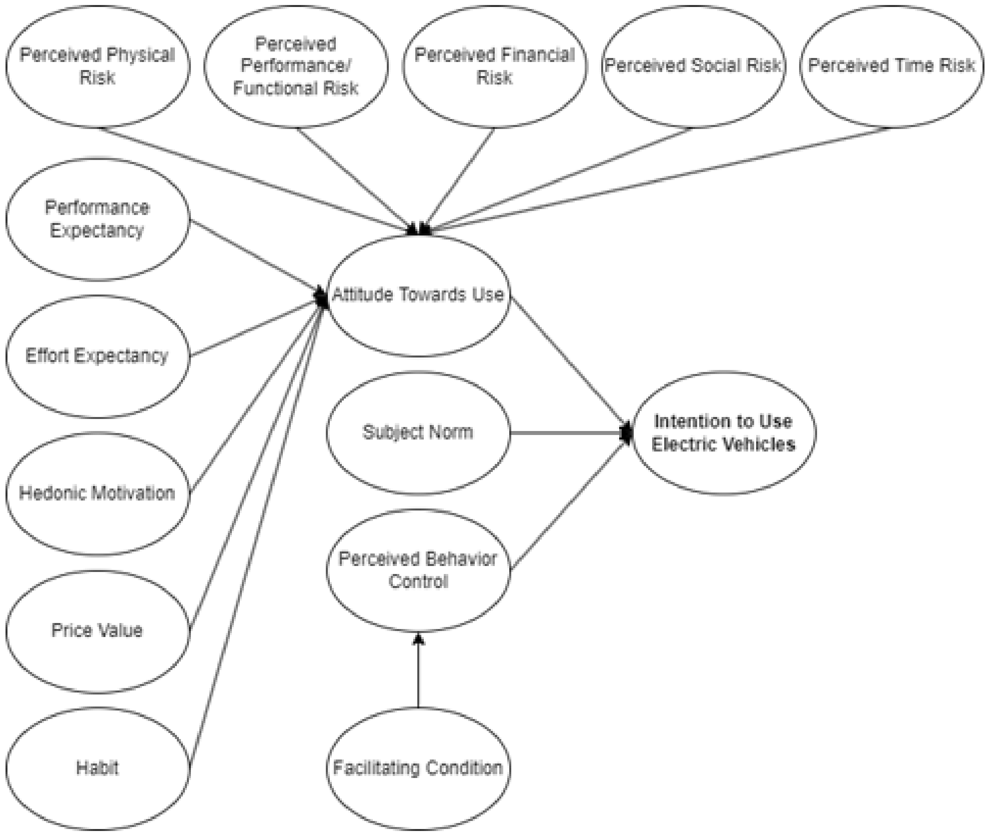

Fig. 1. Original Indonesian EV adoption model [15]

2.2 Government and Industry Support

The interaction between government regulation and industry support is pivotal in the adoption of new technologies. A study [29] constructed an evolutionary model involving a manufacturer and a supplier of Low-Carbon Technology (LCT). The study analyzed multi-phase LCT investment strategies under government reward and punishment regulations, finding that such regulations effectively motivate supply chain firms to invest in LCT.

Another study [30] uses a vector autoregressive model (VAR) and a vector error correction model (VECM) to analyze the impact of EV policy incentives on EV sales in China from 2012 to 2020. The incentives include monetary, privilege, demonstration, and charging incentives. The study finds that in the short term, monetary incentives and administrative controls, such as purchase subsidies, tax exemptions, and vehicle purchase restrictions, effectively increase EV demand. However, in the long term, privilege incentives, charging incentives, and demonstration incentives, like no driving or purchase restrictions, improved charging networks, public procurement, and gasoline price, have a more significant impact on EV sales.

In the context of Indonesia, a survey-based study on 859 SMEs was conducted in [31]. The study used SEM-PLS to analyze the data and highlighted the importance of eco-regulation and government support in promoting eco-innovation adaptation among SMEs. It was also found that eco-environmental factors mediate the relationship between eco-regulation, government support, and eco-innovation adaptation.

Collectively, these studies underscore the nuanced relationship between government policy and industrial response in the context of green technology adoption. They suggest that while government regulations can drive the adoption of green technologies, the perceived value and the specific design of these regulations play a significant role in their effectiveness. Moreover, the industry's response to these regulations, whether through voluntary adoption or as a reaction to economic incentives, is equally important in the successful implementation of green technologies.

2.3 Promoting Regulations for BEVs Adoption

The regulatory environment in Indonesia is progressively evolving to facilitate the widespread adoption of Battery Electric Vehicles (BEVs). Furthermore, empirical research underscores the pivotal role of governmental policy interventions in accelerating the uptake of Electric Vehicles (EVs), as evidenced by the findings in [32, 33]. The cornerstone of this framework is President Regulation Number 55 of 2019, which serves as the principal legal directive for incentivizing both consumers and manufacturers within the BEV domain.

Additionally, a suite of tax incentives has been established to encourage BEV usage, as delineated in various regulations including the Governor of Jakarta Regulation Number 3 of 2020, Government Regulation Number 74 of 2021, and a series of Minister of Home Affairs Regulations (Numbers 1 of 2021, 82 of 2022, and 6 of 2023), culminating in the Minister of Finance Regulation Number 38 of 2023.

Complementing these fiscal measures are government initiatives that provide support for the conversion from ICEVs to BEVs, as specified in the Minister of Energy and Mineral Resources Regulation number 3 of 2023. Furthermore, the State Electricity Company (Perusahaan Listrik Negara) offers discounts for home electricity system installations to BEV adopters, as indicated in their press releases No. 139.PR/STH.00.01/III/2022 and No. 046.PR/STH.00.01/I/2023.

2.4 Agent Based Modelling in Alternative Technology Adoption

To explore and the empirical factors underlying the adoption of BEVs in Indonesia, the utilization of ABM simulations offers a valuable avenue for elucidating how systems may respond to novel circumstances. ABM employs autonomous entities characterized by dynamic behaviors and diverse attributes, with these agents interacting among themselves and with their environment. Consequently, emergent outcomes at a macroscopic level ensue, enabling quantitative analysis of complex systems [34]. Thus, ABM serves as an apt simulation technique for depicting the diffusion process of innovation within a specific population [35].

There are four main assumptions imposed by ABM [36]:

1. Agents are autonomous
2. Agents are interdependent
3. Agents follow simple rules
4. Agents are adaptive and backward-looking

Agent-Based Modeling (ABM) has emerged as a valuable tool for simulating the adoption of various new technologies through the application of diverse algorithms. This study represents a notable advancement, building upon the foundation laid in [37], wherein both variance theory and processual theory are integrated within an ABM framework. Specifically, the research combines the TPB—a variance theory focusing on adoption at a specific moment—and the DOI—a processual theory that captures the dynamic nature of technology adoption over time. In integrating DOI into the model, network effects are considered, thereby representing interpersonal relationships observed in real-world situations. Additionally, the study proposes the integration of ABM with Structural Equation Modeling (SEM), offering a sophisticated approach to account for temporal dynamics. This integration complements the statistical rigor provided by traditional SEM methods, enhancing our understanding of technology adoption processes.

2.5 Conceptual Framework and Research Hypothesis

To integrate the adoption model proposed in [15], this research necessitates refining the model by dividing it into two distinct components: intention to use electric vehicles (EVs) and barriers to using EVs. Consequently, a modified framework accommodating this change is employed, as illustrated in Fig. 2. The rationale behind this division lies in the fact that agents, when making adoption decisions, must overcome specific barriers. While the writer may have initially assigned arbitrary values to serve as these barriers, it is essential to emphasize that these values lack empirical grounding. Some studies posit that perceived risk is one of the main barriers preventing individual's adoption of EVs [38, 39, 40]. In this study, the perceived risk identified in [15] is considered as a barrier to adoption.

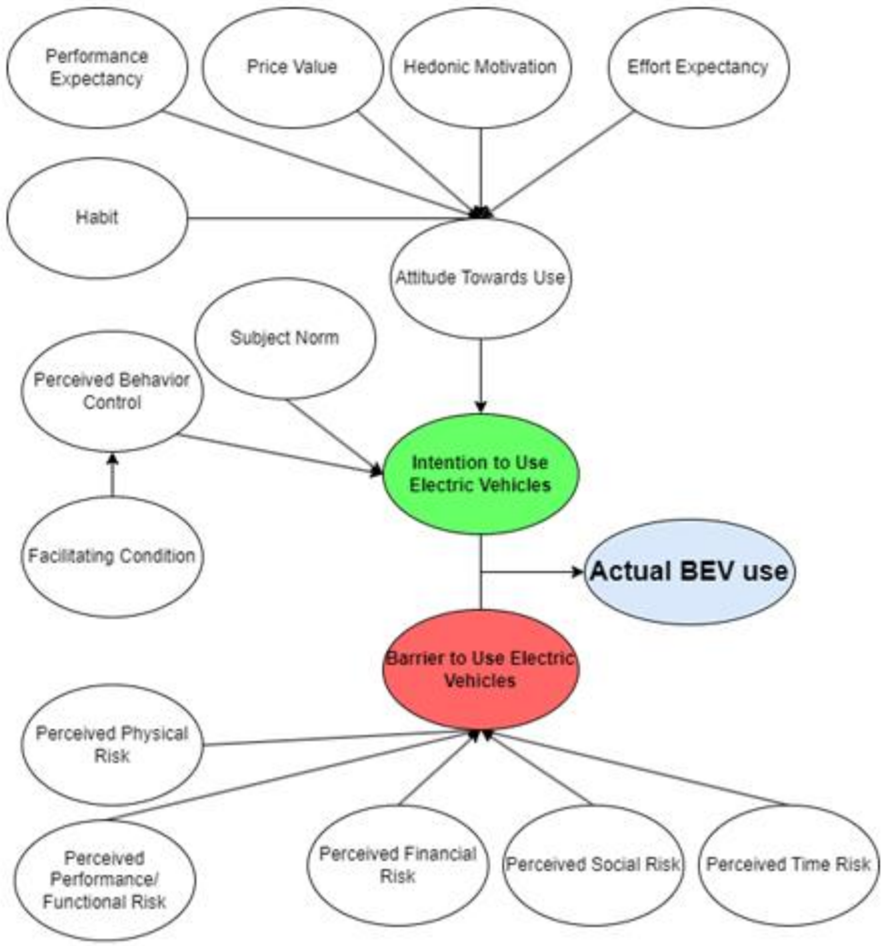

Fig. 2. Modified conceptual model for use in ABM simulation.

III. METHODOLOGY

This research employs a quantitative approach by developing an ABM simulation. The study draws upon the EV adoption model previously developed in [15] as shown in Fig. 1, which has undergone validation through the Structural Equation Method.

Subsequently, an ABM simulation was developed utilizing Netlogo 6.3.0. The model draws inspiration from prior studies that integrated variance and process models into ABM [37].

In each simulation round, which corresponds to a year of vehicle sales, a cohort of agents is generated to represent motorized vehicle buyers for that year. Each agent possesses two output values: intention to use and barrier to use. If an agent's intention to use surpasses a certain threshold, they opt for BEVs over Conventional Vehicles. These output values are influenced by determinants outlined in [15]. However, to reflect the current context, this study introduces multiplicative factors to some of these determinants.

Agents who have already adopted BEVs can positively impact the subjective norm determinant of those around them, and those in their social connections. This modeling approach simulates real-world social relationships, such as interactions with neighbors, fellow road users, family members, and friends. Additionally, the model incorporates a simulated city environment where a percentage of the population is densely concentrated, ensuring that each agent has a higher number of nearby neighbors.

Furthermore, during each simulation round, an 'influencer' agent is introduced. Agents linked to influencers who have adopted EVs also experience positive influence on their subjective norm determinant. Similarly, agents positioned within media influence zones are affected by media representations.

The model incorporates four critical variables for scenario settings: government support, BEV performance changes, BEV price value adjustments, and industry support. These variables are represented as multipliers. During model calibration, this study assigns specific values based on available data concerning the current state of the BEV market and the regulatory landscape.

In the context of government support, quantification relies on the annual normalized count of active regulations in Indonesia specifically designed to promote BEVs. This quantified value exerts a positive influence on subjective norms, attitudes toward BEV adoption, and facilitating condition determinants, while concurrently impacting the financial risk determinant negatively.

Regarding performance change, this study utilizes data processed in [41], sourced from the US Environmental Protection Agency. The processed dataset represents the median range of available BEVs in the market for each year. Subsequently, the data undergoes normalization, serving as multiplying factors that influence the performance expectancy determinant annually.

As for BEV price value change, the assumption is that it will progressively increase over time. This evolving value collectively affects each agent’s price value determinant. For calibration purposes, this study adopts a value of 0.1 increase in each round of simulation based on the coefficient derived from the linear trendline of median BEV range data.

Industry support, on the other hand, finds quantification through the normalized count of available BEV models offered for sale each year. This value positively affects the facilitating condition determinant, working in conjunction with government support.

Fig. 3 shows how the simulation would work. The algorithm is structured into two distinct levels: the global level and the agent level. At the global level, the initial step involves setting up the technological conditions and external factors that will influence the adoption process. This establishes the overarching environment in which the agents will operate.

Subsequently, at the agent level, new agents are spawned into the simulation. Each agent is assigned intrinsic behavioral characteristics and perceptions towards BEVs, reflecting the heterogeneity of individual preferences and attitudes. The algorithm then records the network adoption of BEVs and relevant external factors, capturing the current state of the system. This data serves as a baseline for subsequent iterations.

A key component of the algorithm is the comparison of the intention to adopt BEVs with the barriers to adoption for each agent. This comparison is represented by the expression "Intention vs. Barrier" and serves as a decision criterion for agents to either adopt a BEV or not.

If an agent decides to adopt a BEV, the algorithm updates the external factors to reflect the changing dynamics of the system. Conversely, if an agent decides not to adopt, the external factors remain unchanged for that iteration. To track the progress of the simulation, the algorithm records the number of adopters in each run. This data can be analyzed to identify patterns and trends in the adoption process.

The algorithm then evaluates whether the desired simulation length has been reached. If not, the process loops back to the agent level, incorporating the updated external factors from the previous iteration. This iterative process continues until the predetermined simulation length is achieved, allowing for the exploration of dynamic interactions between agents and their environment over an extended period.

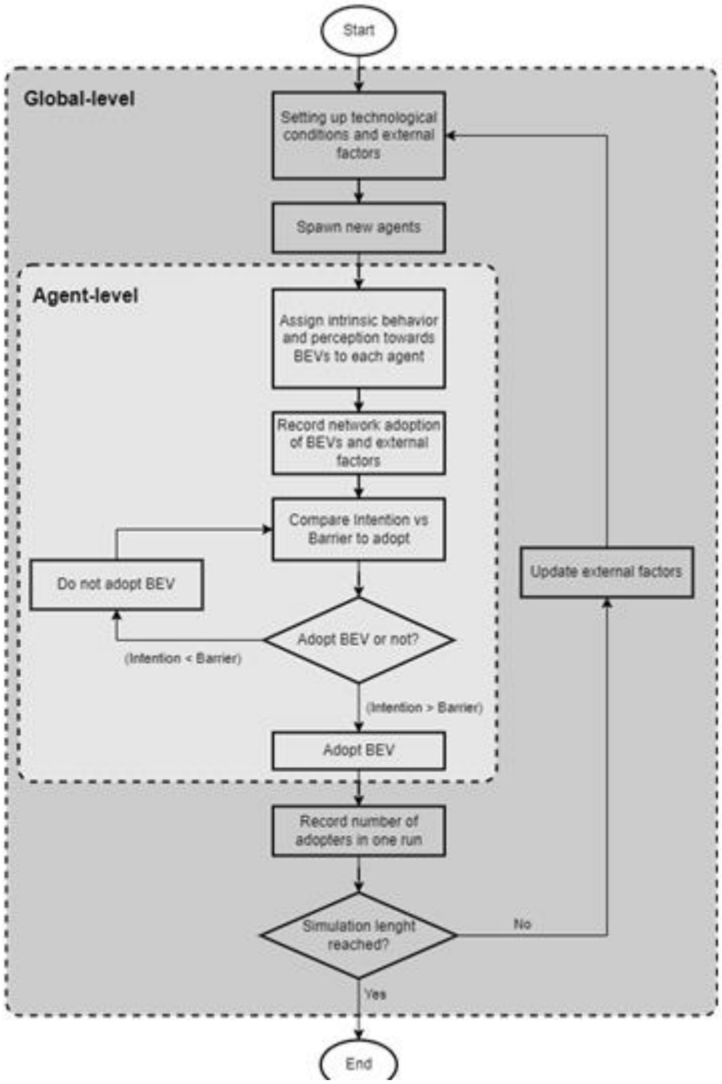

Fig. 3. Simulation model flowchart

There are four main approaches to calibrating agent-based models: direct, indirect, Werker-Brenner, and history-friendly [42]. Direct calibration involves directly using empirical data to parameterize the model, while indirect calibration identifies parameter spaces from empirical data that replicate relevant stylized facts. The Werker-Brenner approach calibrates initial conditions and a range of model parameters using empirical data. In contrast, the history-friendly approach ensures that parameters, interactions, and decision rules align with empirically observable historical data, such as causal, historical, and anecdotal knowledge. This study adopts a direct calibration approach [42], utilizing empirical data extracted from GAIKINDO annual car sales reports spanning from 2018 to 2023 to directly parameterize the model. This calibration process yielded a multiplication factor, thereby refining the model and resulting in a more robust simulation outcome. The calibration is done to consider pockets of populations that absolutely have no means of adopting BEVs such as in frontier regions. Subsequently, a series of diverse scenarios were meticulously generated by systematically manipulating government support, BEV performance changes, BEV price value adjustments, and industry support.

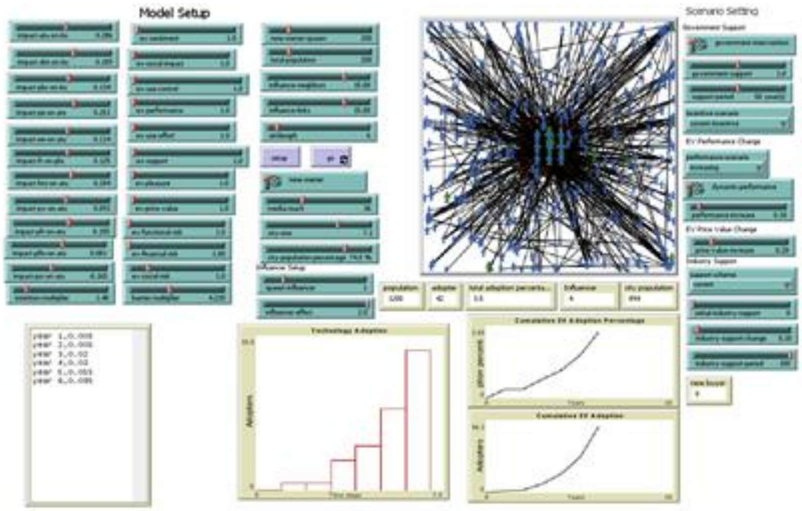

Fig. 4. Simulation interface

2.1 Scenario Setting

Upon completing the calibration phase, this study will proceed with a series of experiments utilizing a simulation framework. The primary objective is to examine the impact of various factors on the adoption patterns of electric vehicles (EVs). Specifically, we will investigate how government support, EV performance dynamics, EV price-value dynamics, and industry backing influence adoption behavior.

To achieve this, several distinct scenarios are constructed, each characterized by varying multiplication factors. These factors serve as indicators of aggressiveness in promoting battery electric vehicles (BEVs). The scenarios span a spectrum from conservative to progressive approaches. The specific configuration of these scenarios is outlined in Table 2.

Table 2. Scenario variables value settings

Regulation (Subsidy) (SBN)		**Vehicle Performance (PE)**		**Price value (PV)**		**Support (FC)**	
Parameter setup	**Value**	**Parameter setup**	**Value (increase)**	**Parameter setup**	**Value (increase)**	**Parameter setup**	**Value**
Calibration	varying (number of active supporting regulations	Calibration	0.1	Calibration	0.1	Calibration	varying (number of BEV car models)
Aggressive	0.2	Aggressive	0.15	Aggressive	0.15	Aggressive	0.2
Conservative	0.1	Conservative	0.05	Conservative	0.05	Conservative	0.1

In subsequent sections, we will employ the values presented in this table as guidelines for our experimentation using the ABM simulation. These scenarios are designed to simulate agent responses to changes in relevant variables. To facilitate this investigation, Table 3 provides a comprehensive overview of the scenarios, illustrating how they align with specific alterations in the model's parameters.

Table 3. Experiment scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Regulation (subsidy)	Aggressive	Aggressive	Conservative	Conservative
Industry Support	Aggressive	Aggressive	Conservative	Conservative
Vehicle performance	Aggressive	Conservative	Aggressive	Conservative
Price value	Aggressive	Conservative	Aggressive	Conservative

This study posits that government regulations and industry support work together. Furthermore, it considers vehicle performance and price value to be mutually aligned. In Scenario 1, aggressive support from both industry and government is simulated alongside significant BEV technological advancements. Scenario 2 mirrors this aggressiveness but assumes a lagging pace of BEV advancement. Conversely, Scenario 3 reverses the dynamic of Scenario 2, depicting rapid technological advancement without concurrent support from government and industry. Finally, Scenario 4 models an overall conservative stance towards BEV adoption, reflecting minimal support and enthusiasm from both sectors.

IV. RESULTS AND DISCUSSION

4.1 Calibration Results

For calibration purposes, this study relies on annual wholesale data compiled by Gaikindo from 2018 to 2023. These data points serve as a robust benchmark for comparison against the baseline scenario. As discussed in the preceding chapter, four pivotal variables dictate the specific scenarios employed: government support, BEV performance changes, BEVs price value adjustments, and industry support. This process leverages current conditions as a foundation for establishing values for these four critical variables.

The calibration process involves determining the multiplication factor values for intention and barrier to electric vehicle adoption. Multiple iterations were conducted until the shape of the adoption pattern aligned closely with BEVs wholesale data. However, it was observed that the simulation results exhibited excessive optimism compared to real-world conditions as shown in Table 4. Consequently, after identifying the closest adoption pattern, the results were further adjusted by introducing a division factor. The chosen division factor was obtained by finding the median of division factor from year 4 to year 6. This adjustment ensures that the simulation outcomes closely mirror empirical data which are shown in Table 5 and Fig. 5 for graphical representation of the data.

Table 4. Baseline scenario results

Raw Simulation		**Empirical Data**		**Division Factor**
Period	**Result**	**Year**	**BEV Marketshare**	
year 1	0.50%	2018	0.00%	Undefined
year 2	0.50%	2019	0.00%	Undefined
year 3	2.50%	2020	0.02%	106.41
year 4	3.40%	2021	0.08%	43.88
year 5	4.43%	2022	0.99%	4.50
year 6	7.73%	2023	1.70%	4.56
Intention multiplier		**1.723**		
Barrier multiplier		**5.2**		

Table 5. Adjusted simulation results

Chosen Divider Factor	**Year**	**Adjusted Simulation Results**	**Error**
4.56	2018	0.11%	-
	2019	0.11%	-
	2020	0.55%	-95.72%
	2021	0.75%	-89.62%
	2022	0.97%	1.27%
	2023	1.70%	0.00%

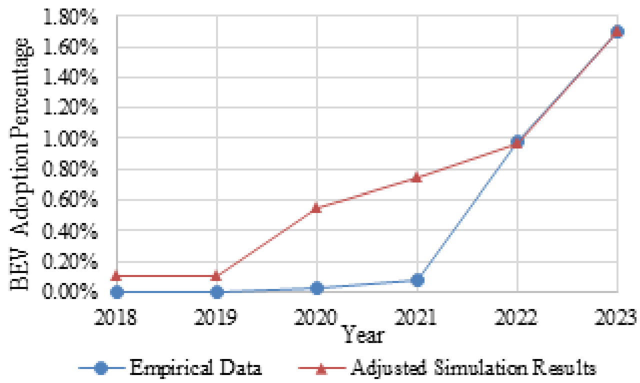

Fig. 5. Comparison graph between empirical and simulation data

The calibration results demonstrate that the ABM simulation closely mirrors the real-world adoption patterns of BEVs in Indonesia, particularly evident in the years 2022 and 2023. To enhance the robustness of our experiments, the obtained results are divided by a factor of 4.56 to achieve greater precision and reliability.

4.2 Scenario Analysis

Scenario analyses were undertaken, with each scenario undergoing 30 cycles of simulations, mirroring a 30-year timeframe of BEV adoption in Indonesia. This systematic approach allows for a thorough exploration of potential adoption trajectories over an extended period. The outcomes of each simulation are depicted in Fig. 6, providing visual representation of the results.

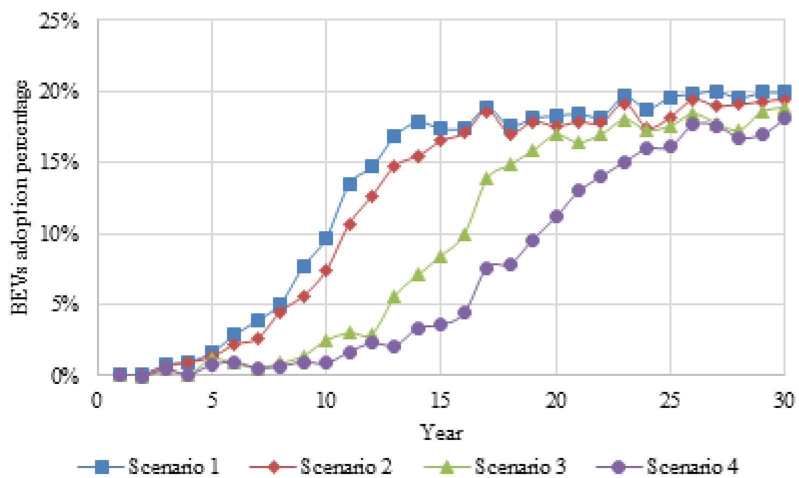

Fig. 6. Simulation results of BEV adoption projection in Indonesia

The primary distinction between Scenarios 1 and 2 lies in the vehicle performance and price value. In Scenario 1, these parameters are set aggressively, while in Scenario 2, they are set conservatively. Both scenarios exhibit a striking similarity, reaching saturation significantly earlier than Scenarios 3 and 4. A substantial divergence is observed when the regulatory and industry support are set to conservative in Scenarios 3 and 4.

To delve deeper into these dynamics, additional simulations were conducted under the premise of a discord between government and industry, with the specific settings detailed in Table 6. This was undertaken to determine if any significant disparities would emerge under these conditions.

Table 6. Additional scenarios

	Scenario 5	Scenario 6	Scenario 7	Scenario 8
Regulation (subsidy)	Aggressive	Conservative	Conservative	Conservative
Industry Support	Conservative	Aggressive	Conservative	Conservative
Vehicle performance	Conservative	Conservative	Aggressive	Conservative
Price value	Conservative	Conservative	Conservative	Aggressive

In Scenarios 5 and 6, the parameters for vehicle performance and price value are conservatively set to minimize their impact on the discord between regulatory and industry support. Additionally, Scenarios 7 and 8 were introduced to investigate the adoption pattern should discrepancies arise between vehicle performance and price value.

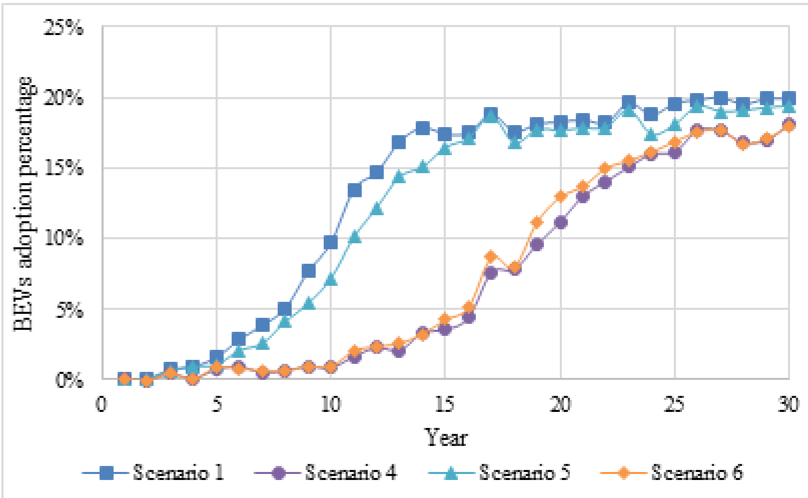

Fig. 7. Simulation results in case of government-industry inconsistency

Scenarios 1 and 4 are retained in Fig. 7 as benchmarks for the upper and lower limits of the simulation. The results indicate that Scenario 5 approaches saturation slightly slower than Scenario 1, while Scenario 6 closely mirrors Scenario 4. This suggests that government regulation may have a predominant influence on the BEV adoption pattern in Indonesia.

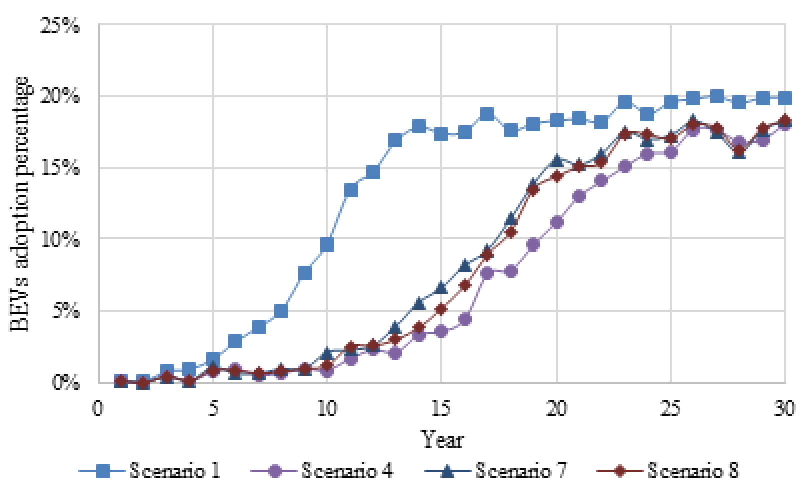

Fig. 8. Simulation results in case of price-performance inconsistency

Contrary to previous results, there is no significant difference between Scenarios 7 and 8. This could imply that increases in price value and advancements in BEV performance exert similar effects on BEV adoption.

4.3 Discussion

The model, developed in this study, was conceptualized, and designed to serve as an alternative tool, with the primary objective of facilitating the prediction of the adoption of emerging technologies. In this instance, the focus is on the adoption of BEVs. This model is not merely a standalone tool, but also incorporates SEM verified model. The integration of the SEM model, which has been tested and validated, allows for the generation of informed and educated predictions. These predictions are made possible through the application of ABM simulation. In the process of calibrating this simulation, the global settings in the simulation are made to adequately reflect the current condition in Indonesia, particularly with respect to the support for BEVs, regulatory frameworks, and advancements in BEV technology. The results of the simulation revealed significant discrepancies between the simulated outcomes and the empirical data, as illustrated in Table 5, during the years 2020 and 2021. It is noteworthy that these years coincided with a period of heightened social restrictions and economic downturn in Indonesia due to COVID-19 pandemic. These circumstances mirrored in the country's Gross Domestic Product (GDP) growth rates, which were -2.07% and 3.70% respectively [43]. These figures are markedly lower than those recorded in other years, underscoring the impact of these conditions on the adoption of BEVs.

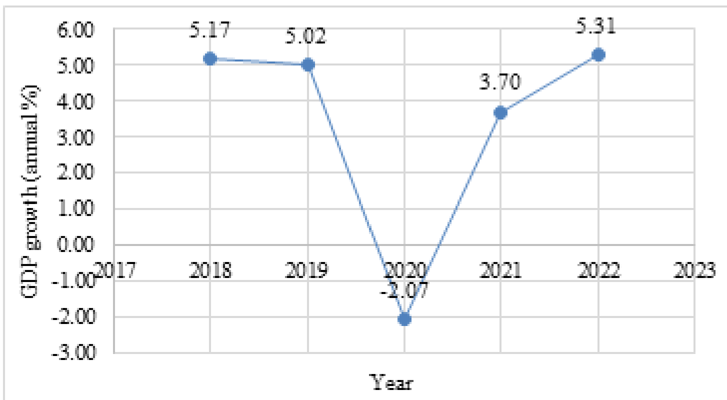

Fig. 9. 2018-2022 annual GDP growth of Indonesia [43]

This temporary economic decline due to COVID-19 pandemic aligns with the findings of prior research [44, 45]. This alignment may suggest a strong influence of macroeconomic conditions on the widespread adoption of BEVs. The rationale behind this assertion is that the model, in its current form, does not incorporate alterations attributable to macroeconomic conditions. Consequently, the model's predictions may not fully capture the real-world complexities of BEV adoption during periods of economic instability.

Upon the completion of the calibration process, this study explores the various factors that influence the adoption pattern of BEVs in Indonesia. These factors include government regulations, industry support, the performance of BEVs, and the perceived price value of BEVs. In the initial run of the simulation, a comparison was made among four distinct scenarios. It was hypothesized in this context that government regulation and industry support operate in harmony. The outcomes, as depicted in Fig. 6, indicate that the combined effect of government regulation and industry support exerts a substantial influence on the adoption patterns of BEVs. This influence appears to be more pronounced than that of the advancements in BEV technology or the escalation in the price value of BEVs. This finding underscores the critical role of regulatory and industry support mechanisms in fostering the adoption of green technologies.

Further simulation is done with new assumptions that there is discord between government regulation and industry support. The results cemented that government regulation has overarching effect on BEVs adoption in Indonesia. This is in line with previous studies on how government regulation really drives up adoption of new technologies (Achmad et al., 2023). However, it is inconclusive if the synchronization of government incentives and industry support have noticeable implications as shown in previous studies (Liu et al., 2022; Liu et al., 2023).

V. CONCLUSION

This study shows that integrated model, combining the strengths of SEM and ABM, provides a reliable framework for predicting BEV adoption patterns. This, in turn, may contribute to the understanding and promotion of sustainable transportation solutions.

To enhance the accuracy and comprehensiveness of BEV adoption trends, future models could consider incorporating macroeconomic variables. The inclusion of these factors could augment the model's predictive power, making it a valuable tool for policymakers and stakeholders in the green technology sector. Ultimately, this could lead to the formulation of more effective strategies for promoting the adoption of BEVs and other green technologies, especially during periods of economic uncertainty.

This study also underscores the influential role of government regulation in BEV adoption, particularly in terms of incentives and support. However, it is important to note that BEVs should not be viewed as the sole solution for reducing environmental impact in the personal motorized vehicle sector. Several studies suggest that Hybrid Electric Vehicles (HEVs) have a smaller carbon footprint than BEVs [46, 47, 48]. Despite this, HEVs have not received the same level of success or support as their fully battery-powered counterparts in Indonesia.

Future research studies might delve deeper into the intricate details of customer preferences, exploring the various factors that influence their choices between different alternatives to Internal Combustion Engine Vehicles (ICEVs). These alternatives could include, but are not limited to, Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), and Fuel Cell Electric Vehicles (FCEVs). Such studies could provide valuable insights into the driving forces behind consumer decisions, potentially revealing patterns and trends that could guide the development and marketing of these sustainable transportation options.

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