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When and why does transition fail? A model-based identification of adoption barriers and policy vulnerabilities for transition to natural gas vehicles

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Abstract

Natural gas vehicles (NGV) face significant adoption barriers in Jakarta. Therefore, a successful transition requires measures from the government. Owing to the high cost of transition policies, the efficacy of these policies must be analyzed to identify the most effective policy. The implementation of transition policies, however, could dynamically influence people's perception and behavior, which then changes the landscape of adoption barriers. Furthermore, even a seemingly successful policy may fail when a certain pathway of uncertainties emerges in the future. To address these concerns, we integrated agent-based modeling, exploratory modeling, and diffusion of innovation theory into the exploratory model-based diffusion analysis approach. This approach evaluates the policy's performance, explores changes in the relative importance of different adoption barriers, and identifies policy vulnerabilities, i.e., scenarios leading to policy failures. We tested this approach on four NGV transition policies targeting three adoption barriers. We found that the importance of adoption barriers and the critical uncertainties upon the implemented policies. The social–behavioral barrier predominates under current conditions, whereas the economic factor becomes more relevant when all policies are executed. Understanding the changes in adoption barriers and policy vulnerabilities will help decision-makers to prepare additional measures that ensure a successful transition.

Keywords: Adoption Barriers, Technology Diffusion, Exploratory Modelling, Policy Vulnerabilities, Natural Gas Vehicles

1 Introduction

Concerns related to energy security have encouraged the Indonesian government to promote energy diversification (Erahman et al., 2016). Since the late 1980s, the Indonesian government has introduced natural gas vehicles (NGV) as a clean alternative to gasoline and diesel vehicles (Hartanto et al., 2012). The aim was primarily to reduce the consumption of fossil fuels and CO_2 emissions in the transportation sector. Several policies were implemented by the Indonesian government to support the uptake of NGV, including enforcing regulations on securing gas supply, controlling gas prices, and accelerating the development of gas refueling stations (Hartanto et al., 2012; Sopha et al., 2017). Despite extensive efforts, the increase in the usage of NGV in Indonesia has been quite slow, which can be confirmed by the minimal increase in the number of NGV (Sopha et al., 2017). At present, there are ~5690 NGVs in Indonesia, which is significantly lower in comparison to other Asian countries, such as India (~1,800,000), Pakistan (~2,790,000), and Iran (~3,500,000) (NGVJournal, 2014). Barriers such as social, economic, and technological factors have been the primary reasons behind this discouraging outcome (Hartanto et al., 2012).

NGV adoption in Indonesia reflects a complex dynamic process. It also represents a socio-technical transition of technology diffusion, encompassing the embeddedness of technology within its broader systems of practices (Jacobsson & Bergek, 2011). Technology diffusion involves multisector interdependencies carrying related uncertainties and risks (Raven & Verbong, 2007). Hence, despite the implementation of specific policies and strategy development, barriers may expand, new problems may arise, and undesirable social, economic, and environmental consequences may emerge during the diffusion process. The diffusion of innovation (DOI) theory captures the socio-technical transition phenomena by specifying several factors contributing to technology adoption: the adopters' characteristics, technology attributes, communication channels, and decision-making processes (Rogers, 2010). Potential adopters can be typically classified into five categories, depending on their willingness to purchase new technology: innovators, early adopters, early majority, late majority, and laggards (Robertson, 1967). These categories show that adopters play different roles in triggering the diffusion in a given market; therefore, their attitudes are crucial to the diffusion process (Im et al., 2003). For this reason, adopters' decision-making behavior has received considerable attention in socio-technical transitions studies (Farmer & Foley, 2009; Im et al., 2003).

Socio-technical transitions have been studied using different approaches. Within transitions research, socio-technical transformations have been extensively formulated or modeled using various transition modeling approaches (Bergman et al., 2008; Köhler et al., 2018a). Agent-based modeling is among of the most widely used approaches (Bergman et al., 2008; Holtz et al., 2015; Köhler et al., 2018a; Rahmandad & Sterman, 2008). Agent-based modeling captures the heterogeneity of adopters and models the dynamics of micro-level decision-making and the interactions between actors (Bonabeau, 2002; Farmer & Foley, 2009). Among the different socio-technical transition studies, this approach has been extensively applied to diffusion of new energy technologies (Hansen et al., 2019) such as electric cars (Noori & Tatari, 2016; Wolf et al., 2015), solar PV and battery systems (Palmer et al., 2015; Rai & Robinson, 2015), and micro-cogeneration (Faber et al., 2010). Additionally, transitions in the mobility sector have been investigated using agent-based modeling as well (Köhler et al., 2018b; Köhler et al., 2009; Moallemi & Köhler, 2019). Most of these studies were intended to elucidate adoption barriers and to explore the effectiveness of alternative transition policies.

To date, very few studies on NGV adoption in Indonesia have examined both the barriers and potential supporting policies for adoption. Hartanto et al. (2012) discussed the development and barriers of NGV adoption in Indonesia. Using the agent-based modeling approach, Sopha et al. (2017) explored policy options that support NGV adoption by examining the decision-making processes of adopters. These studies, however, neglected two policy-relevant concerns. First, these studies do not systematically explore nor explain which adoption barriers are to be targeted and affected by alternative transition policies Thorough insights into the existing adoption barriers and their interactions with the heterogeneity of potential adopters are keys to successful adoption of a new technology, including NGV (Tran et al., 2012). A more detailed understanding would empower policymakers to target specific stages in the adoption process, and hence improve the adoption rate.

The second concern is neglecting the uncertainties in the transition dynamics and in the simulation models supporting those transitions, which are often subject to deep uncertainties (Ascough et al., 2008; van Asselt & Rotmans, 2002). Deep uncertainties depict conditions under which policymakers and analysts cannot agree on the relative importance of the outcomes to be considered, do not know or cannot characterize the probability distributions of some variables, and/or cannot concede the underlying relationships among the system variables (Lempert et al., 2003; Walker et al., 2013a). By accounting for deep uncertainties in the analysis, one can identify the vulnerabilities of alternative policies, i.e., the future states of the world in which the policies fail to meet their intended goals (Bryant & Lempert, 2010; Walker et al., 2001). One can also evaluate the policy robustness, i.e., to what extent the policies remain successful in the face of deep uncertainties (Lempert et al., 2006; Maier et al., 2016; McPhail et al., 2018). When deep uncertainties are ignored and simplified in model-based analyses, the resulting policy recommendations will most certainly fail if the future uncertainties materialize differently from those of the model assumptions (Haasnoot et al., 2013; Lempert, 2002; Schweizer, 2018; Walker et al., 2013b).

Deep uncertainties inherently exist in models that analyze transitions to and adoption of new technologies (Moallemi et al., 2017; Moallemi & Köhler, 2019; Noori & Tatari, 2016). For example, the survey data of consumer behavior fed to a model do not always extensively capture the consumers' heterogeneity (McCoy & Lyons, 2014). Moreover, these models are developed by competing agent-level decision-making theories, such as planned behavior theory (Ajzen, 1991; Kowalska-Pyzalska et al., 2014; Rai & Robinson, 2015), utility functions (Palmer et al., 2015; Sopha et al., 2017), and the consumat approach (Jager et al., 2001; Janssen & Jager, 1999). The model structure may conceivably depend on the selected decision-making framework. To account for deep uncertainties in model-based analysis, researchers have proposed the Exploratory Modeling and Analysis (EMA) approach (Bankes, 1993; Bankes, 2002; Kwakkel, 2017; Kwakkel & Pruyt, 2013; Moallemi & Malekpour, 2018; van Asselt & Rotmans, 2002). The EMA proposes that a model be used for exploratory purposes rather than for prediction. Specifically, a user of this approach conducts large-scale computational experiments of the model by sampling and searching over the plausible uncertainty space, and then systematically explores the space of model outcomes. Sampling techniques and machine learning algorithms are the primary components of this approach.

To address the abovementioned concerns, we aim to examine the effectiveness and vulnerabilities of alternative policies by considering the case of NGV diffusion in Jakarta, Indonesia, as a case study. For this purpose, we introduce the exploratory model-based diffusion analysis (EMBDA) approach, which integrates agent-based modeling, DOI theory, and exploratory modeling to identify dominant adoption barriers and policy vulnerabilities under deep uncertainties. Generally, agent-based modeling is employed to evaluate the performance of alternative policies, explore changes in the adoption barriers resulting from policy implementation, and assess the vulnerability of each policy alternative to deep uncertainties. In this study, the agent-based model is built on the DOI theory. Furthermore, the exploratory modeling approach is used to generate computational experiments on top of the model to embrace deep uncertainties.

The remainder of this paper is structured as follows. In Section 2, we explain the methodology used to examine the case study and how it is applied. In Section 3, we present and discuss the results of the study. In Section 4, we discuss the conclusion and policy implications of the study.

2 Methodology

To evaluate the consequences and vulnerabilities of alternative transition policies, we apply the exploratory modeling and analysis (EMA) approach to an agent-based model of technology diffusion. The model is built on the DOI theory, in which agents proceed through certain stages of adoption (Rogers, 2010). EMA is applied to generate computational experiments for this model and to evaluate the results (Kwakkel, 2017; Kwakkel & Pruyt, 2013). This approach allows for embracing deep uncertainties, which are ubiquitous in technology diffusion problems (Lempert, 2002). We integrate agent-based modeling, DOI theory, and EMA into the EMBDA approach, as shown in Figure 1. We follow this approach to evaluate alternative transition policies for NGV adoption in Jakarta.

[Figure 1 here]

2.1 Agent-based model description

In Jakarta, most NGVs are private cars that have been converted from gasoline or diesel. Accordingly, the agent-based model accounts for the heterogeneity of the socio-economic background and the geographical location of car owners. It comprises the agents' properties, their actions, and alternative transition policies by the government. The agents' properties are categorized into states (i.e., their stage of adoption) and attributes (e.g., their socio-economic background) (Van Dam et al., 2012). Of core importance in an agent-based adoption model is the conceptualization of adoption barriers. By evaluating numerous agent-based adoption studies, Hesselink and Chappin (2019) reported that the barriers considered in such studies could be categorized into structural, economic, social, and behavioral factors. Accordingly, we consider the same categories of adoption barriers in the model.

New vehicle technology often requires different types of fuel. Accordingly, in agent-based modeling studies on the adoption of new vehicle technology, the structural barrier that is most considered is the availability of the fuel supply infrastructure (Huétink et al., 2010; Sweda & Klabjan, 2011). The lack of infrastructure would cause inconvenience to potential adopters, preventing them from adopting the new technology. The economic barrier comprises an upfront purchasing cost and the expected relative savings from the operational cost (Sierzchula et al., 2014). The latter depicts the difference in the maintenance cost and the fuel price between the new and the old technology. Both social and behavioral barriers are closely interlinked. The social barrier is primarily concerned with the agents' interactions with their social network (e.g., homophily and conformity as considered by Eppstein et al. (2011). The behavioral barrier is concerned with the agents' ignorance because of information unavailability, which was also affected by their social network.

To simplify the complex phenomenon of NGV transition in Jakarta, we make three major assumptions. First, we assume that car owners adopt NGV by upgrading their gasoline car using converter kits rather than buying a new car; hence, the investment cost is the purchasing price of the converter kit. In Jakarta, this technology is preferred because it allows car owners to revert to gasoline-powered vehicles. Second, we assume that the gas and oil fuel prices are constant throughout the simulation. In reality, these prices tend to be constant over three to five years unless there is a major shock in the global market. We ignore such shock scenarios and instead treat the spiked prices as part of the uncertainties. Third, we limit the considered adoption barriers to one or two specific barriers in each of the four barrier categories, i.e., the structural, economic, social, and behavioral factors (Hesselink & Chappin, 2019). The chosen assumptions primarily depend on which details are irrelevant to the policy.

2.1.1 Agent attributes

Car owners are considered as agents in our model. As approximately 3.5 million cars were registered in Jakarta in 2016 (Pardosi et al., 2017), we represent 1000 car owners as a single agent, thus providing a total of 3480 agents in the model. Each agent is characterized by its attributes, i.e., its spatial, socioeconomic, and behavioral properties. To account for the heterogeneity of agents, the values of each attribute assigned to the agents are based on certain probability distributions. Most of these distributions were derived from official and local statistics reports and from previous large-scale transport and commuting surveys (JUTPI, 2012; Pardosi et al., 2017; SITRAMP, 2004). The details of these attributes and the model in general are provided in Appendix A. The description follows the ODD+D protocol (Müller et al., 2013).

The model is spatially explicit to accommodate the structural barrier of NGV adoption. During weekdays, the agents travel to and from their assigned home and work locations. The home location of the agents is spatially distributed across the 42 districts in Jakarta. The spatial distribution is linearly related to the population of the districts, as shown in Figure 2. The agents use the closest NGV refueling station to either their home or work location. The closest NGV refueling station of each agent is annually updated to reflect the building of new refueling stations. Figure 2 shows the locations of the existing NGV and oil refueling stations. As seen in the figure, the NGV refueling stations are dominated by oil refueling stations.

[Figure 2 here]

An important economic attribute of the agents is their monthly income. Because of the lack of detailed information on provincial-level income statistics, this attribute is estimated based on the education background and the age of the agents along with the minimum wage level in Jakarta. Accordingly, the income is annually updated, along with the agents' age. Furthermore, the social–behavioral attributes of the agents include their social network, i.e., with whom they interact, their degree of innovativeness, and the frequency of their interaction.

2.1.2 Agent states and decision-making

Figure 3 shows the five stages an agent undergoes prior to finally adopting an NGV. Among these states, various adoption barriers exist along with the transition phases; some barriers strictly prevent the transition between states (Transition 1 and 3 in Figure 3), while others only delay the transition (Transition 2 and 4). Transition 1 requires agents in the Potential state to be triggered by a "message" from agents in the Adopter state. Adopter agents randomly send the "message" to two of their social networks. This message-triggered transition logic is based on behavioral problems of ignorance and availability bias, which are prevalent in agent-based energy-efficient adoption studies (Moglia et al., 2017).

[Figure 3 here]

Two economic barriers, i.e., Transition 2 and Transition 4, can delay the adoption process. Agents in the Aware state are assumed to know the potential of NGV technology; however, they have not evaluated benefits in detail. Hence, the time required for an agent to move to the Evaluating state is dependent on the perceived economic benefits of adopting the NGV, which is approximated by the ratio of the gas fuel price and the oil fuel price. Once the agent enters the Deciding state, they have a better understanding of the economic benefits of adopting NGV. Thus, the delay time of Transition 4 is dependent on the expected break-even point of purchasing the converter kit (see Table 1 for further explanation).

Transition 3 includes social-behavioral, economic, and structural barriers. Figure 4 shows the decision-making logic within this transition. Agents regularly evaluate these conditions about three times a year. The social–behavioral barrier demands a significant portion of an agent's social network to have already adopted NGV before that particular agent decides to follow the trend. This barrier symbolizes social network adoption and DOI theories. The former reveals that the tendency of an agent to change their behavior increases with the increase in social reinforcement from their network (Centola, 2010). The latter reveals that the social network impact on a person's adoption behavior is dependent on their degree of innovativeness (Rogers, 2010).

[Figure 4 here]

The economic barrier constrains agents from adopting NGV based on their financial capacity to purchase converter kits. The agents' annual income and their willingness to sacrifice their income to purchase converter kits (i.e., their affordability threshold) are important factors of this barrier. Most households in Jakarta spend less than 20% of their income on transportation (Sugiarto et al., 2014); therefore, we assume that the affordability threshold follows a triangular distribution from 7.5% to 12.5%. In addition to the economic barrier, the availability of refueling stations close to the agents' home or work locations epitomizes the structural barrier. Previous surveys have reported that citizens in Jakarta are willing to travel for a maximum of approximately 3.33 to 6.67 kilometers to refuel their cars (JUTPI, 2012; SITRAMP, 2004). If the distance to the nearest refueling station is above this threshold, the agent will be hesitant to adopt NGV, even when the social–behavioral and economic barriers are overcome.

2.1.3 Policy interventions and performance indicators

We evaluate three alternative policy interventions that have been publicly debated for a long time and will likely improve the adoption of NGV in Jakarta. Each policy focuses on different adoption barriers. The alternative policies include distribution of free converter kits, reduction in converter kit purchasing price through subsidies, and construction of new NGV refueling stations. In addition to these policies, this study considers a baseline policy with the following assumptions: (i) at the start of the simulation, seven agents that represent around 7000 NGV in Jakarta are placed directly in the Adopter state, while the rest of the agents are in the Potential state; (ii) the converter kit price starts at IDR 17 million (~$1200) and decreases by 2% each year because of technological advancement; and (iii) there are 13 fully operating refueling stations (Hartanto, 2017), and, according to the central government plan, two additional refueling stations will become operational every two simulation years.

In addition to each individual policy, the combination of all policies is tested, which results in five policy setups:

1. Baseline policy: No additional interventions.
2. Kit subsidy policy: Reducing the converter kits' price by 10%. This policy attempts to offset the economic barrier by making the converter kits more affordable.
3. Free kit policy: Distributing 20,000 free converter kits. In the model, this corresponds to 20 additional agents that enter the Adopter state at the beginning of the simulation. This policy attempts to offset the social–behavioral barrier as there are more adopters.
4. Infrastructure enhancement policy: Substantially accelerating the development of the refueling stations by constructing 70 new refueling stations within ten simulation years. This policy attempts to offset the structural barrier by strengthening the fuel supply infrastructure.
5. Integrated policy: Combination of subsidy policy for kits, free kit policy, and infrastructure enhancement policy.

The model is implemented in AnyLogic simulation package. The simulation is run for 14 years from 2017 to 2030. At the end of the run, two groups of performance indicators are observed. The first one is the number of agents in each adoption state. Of particular interest is the number of agents in the Adopter state and those in the Potential and Evaluating states. A high number of agents in the Potential state indicates a low degree of citizen awareness for NGV; while a high number of agents in the Evaluating state indicates that many car owners failed to overcome the strict adoption barriers. This leads to the second group of indicators, called “the adoption lags.” This group of indicators attempts to unravel the most critical barriers that prevent diffusion. In particular, we record the number of agents in the Evaluating state who fail to meet either the social–behavioral, the economic, or the structural barrier, and we label them as social lags, economic lags, and structural lags, respectively.

2.2 Exploratory model-based diffusion analysis

Embracing deep uncertainties in new technology diffusion problems requires a different approach in the simulation models. One popular approach to support decision-making under deep uncertainties is the EMA approach (Bankes, 1993; Bankes, 2002; Kwakkel, 2017; Kwakkel & Pruyt, 2013), which requires systematic exploration of different uncertainties in model inputs and assumptions in the model structure by generating an ensemble of simulation runs. EMA is a generic approach that is applicable to various modeling paradigms such as integrated assessment models (e.g., Lamontagne et al., 2018; Rozenberg et al., 2014), system dynamics (e.g., Eker & van Daalen, 2015; Hamarat et al., 2014; Moallemi et al., 2017; Pruyt & Kwakkel, 2014), and agent-based models (e.g., Gerst et al., 2013; Greeven et al., 2016; Jaxa-Rozen et al., 2019; Moallemi & Köhler, 2019). While this universal approach can be applied to several cases, a tailored EMA approach specific to model-based diffusion studies has not been reported to date. To address this gap, we combined EMA with the DOI theory and developed the Exploratory Model-based Diffusion Analysis (EMBDA) approach.

2.2.1 Exploratory Modeling and Analysis (EMA)

EMA is the systematic exploration of the impacts of various parametric, structural, and methodological uncertainties on the performance indicators of a simulation model (Bankes et al., 2013). EMA aims at using simulation models not for “prediction,” but rather for “exploration” purposes. EMA comprises three main steps: generation of an ensemble of scenarios, execution of simulation runs on these scenarios and inductive reasoning on the simulation results. Accordingly, the first step in EMA concerns the experimental design of scenarios that span the entire plausible range of model parameters and competing alternative model structures (Islam & Pruyt, 2016; Moallemi et al., 2018). This step uses statistical sampling techniques such as the Monte Carlo or the Latin hypercube sampling (Herman et al., 2015; Kwakkel, 2017).

The next step in EMA entails conducting a backward induction from the simulation results to model parameters and structures using scenario discovery techniques (Bryant & Lempert, 2010; Groves & Lempert, 2007; Lempert et al., 2008; Lempert et al., 2006). These techniques are probability neutral, and they attempt to map the scenarios (input space) to performance indicators (output space) without applying the probabilistic aggregation approaches from the simulation results. Scenario discovery can help in identify policy vulnerabilities, i.e., the condition under which a policy fails to meet its objective (Walker et al., 2001). By analyzing policy vulnerabilities, one can increase the robustness of the policy by formulating further hedging and shaping actions that can safeguard the success of the policy (Dewar, 2002).

Two steps exist in scenario discovery techniques (Bryant & Lempert, 2010). First, the threshold value for the outcomes of interest must be determined. The simulation runs, and their associated scenarios are classified into those whose performance indicators fall below (or above) the threshold and those that do not. In the case of new technology adoption, for instance, a low number of adopters is undesirable. A threshold is thus set at the minimum acceptable number of consumers who adopt the technology. Subsequently, in the second step, the scenario discovery algorithm identifies the combinations of uncertain parameters leading to these undesired outcomes. The Patient Rule Induction Method (PRIM), a bump-hunting algorithm, is most often used for this purpose (Friedman & Fisher, 1999; Lempert et al., 2008). This algorithm maps the simulation results to their corresponding input parameters and then searches for regions within the input space with a high density of undesired simulation results.

Experiments were conducted on the EMA workbench in the Python library (Kwakkel, 2017). The library provides a flexible and user-friendly interface for connecting simulation models to the entire exploratory modeling and analysis steps. The library adopts the XLRM framework (Lempert et al., 2003; Tran & Daim, 2008), wherein users must define the exogenous uncertain variables and their corresponding range of values ('X'), the policy levers ('L'), the system relationships encapsulated in the simulation model ('R'), and the performance measures to be observed ('M'). The library then supports the design, generation, and execution of computational experiments in the simulation model and provides interfaces for visualizing and analyzing the results.

2.2.2 Stages within the EMBDA approach

We combined concepts from the DOI theory and steps within the EMA approach and formulated the EMBDA approach. The DOI theory focused on the importance of understanding both the impact of uncertainties in the system and the dominant adoption barriers and how policy interventions are related to those barriers (Foxon & Pearson, 2008; Hesselink & Chappin, 2019; Raven & Walrave, 2018; Reddy & Painuly, 2004). The EMA approach suggests the use of computational experiments to systematically map the outcomes of interest to the underlying assumptions and uncertainties. Therefore, combining these two concepts results in a three-stage approach, as depicted in Figure 1.

The approach begins with a problem formulation. Besides developing the simulation model, we must clarify three further aspects. First, we must understand the prominent adoption barriers in the context of the study. To identify the most influential barriers, each barrier must be explicitly represented in the model. Next, each specific adoption barrier is attempted to be overcome through the development of policy interventions. Finally, we must identify the uncertainties that are influential to the adoption barriers and the decision-making processes. These uncertainties may originate from agent attributes (such as willingness to pay for new technology), external variables (such as crude oil price), or model structures (such as interaction patterns among the agents).

Table 1 lists the uncertainties considered in the case study. This list encompasses the variables that directly influence the decision-making processes of the agents (see Figures 3 and 4). The value bandwidths of these uncertainties were inferred in two ways. To derive the uncertainties related to economic variables, we used the historical statistics of the variable complemented by a small additional margin. The uncertainties related to the states and behaviors of agents were inferred from transport surveys (JUTPI, 2012; SITRAMP, 2004; Sugiarto et al., 2014), and were also complemented by a small additional margin.

[Table 1 here]

The activities in the problem formulation stage were intertwined in multiple ways, represented using bidirectional arrows in Figure 1. First, one must ensure that the relevant uncertainties, adoption barriers of potential adopters, and policy instruments are explicitly present in the model. If they cannot be explicitly represented, they must be replaced by proxy variables that can epitomize the uncertainties, adoption barriers, and policy interventions. Second, the identification of policy interventions should be based on the adoption barriers, i.e., the adoption barriers targeted by each policy intervention should be clearly delineated. Third, the possibility of uncertainties in (i) the heterogeneity of adoption barriers among the potential adopters, (ii) the effectiveness of policy interventions, and (iii) the structural uncertainties of the simulation models, must be considered. The interrelationships among the activities at this stage imply that the activities should be handled in an iterative way.

The second stage operates the computational experiments. Here, future scenarios are generated based on the identified uncertainties. Specifically, in this study, 2,000 scenarios were created by uniformly sampling across the uncertainty space presented in Table 1. The performance indicators, namely, the number of agents in each adoption state and the number of agents facing different adoption barriers resulting from each policy, are evaluated in each scenario. A total of 10,000 simulation runs were executed in this experimental setup.

The third stage, the vulnerability analysis, gains insights from the results of the computational experiments. The first step in this stage identifies the dominant adoption barrier that emerges when the policies are applied. In agent-based models, the dominant barrier is the barrier that prevents the most significant number of agents from adopting the new technology. Subsequently, the undesired scenarios could be classified based on the identified dominant adoption barrier. For example, if the results of a particular policy indicate that many agents face economic barriers, then the economic barrier for that particular policy would be used as an indicator for undesired scenarios. In our case study, we apply the 75th percentile value of this indicator as a threshold. Note that simulation runs in which the performance indicator score falls above this threshold are characterized as undesirable. Finally, the scenario discovery algorithm is executed to identify the uncertainty space that causes undesired scenarios.

The policy-relevant insight obtained from the third stage supports the design of additional policy packages to further improve the success of the adoption. Policymakers can consider additional measures to increase the adoption rate of the new technology after examining the identified adoption barriers. Moreover, they may use the identified uncertainty space from the scenario discovery algorithm for this purpose. These measures can then be implemented in the model, and the same EMBDA steps can be followed. Finally, the information obtained regarding changes in the landscape of the adoption barriers can guide future studies that explore specific adoption barriers in further detail.

3 Results and Discussion

We generated 2000 scenarios and tested the impact of alternative policies in each scenario. As a result, we conducted a total of 10,000 simulation runs. We evaluated the results in terms of the number of agents in each adoption state at the end of the simulation. Figure 5a–c shows the number of agents in different adoption states resulting from the implementation of each policy alternative, while Figure 5d shows the percentage of agents in each adoption state. In Figure 5a–c, we focused on the Potential, Evaluating, and Adopter states as the transition in the other two states (Aware and Deciding) are only hindered by time delays. Logically, the number of agents in the Aware and Deciding states is substantially lesser than the number of agents in the Potential and Evaluating states (Figure 5d).

[Figure 5 here]

As expected, the integrated policy resulted in the highest number of adopter agents (Figure 5c) with a median value of 901.5 agents (901,500 cars). However, the distribution of the number of adopter agents from this policy has the widest dispersion compared to those resulting from other policies. This indicates that uncertainties have a more profound influence on the success of this policy than on the success of other policies. Within this policy, for 25% of the entire scenario ensemble, there are more than 1,400 adopter agents. Hence, these results show that the integrated policy has the potential to substantially increase the adoption of NGV or even make it reach a tipping point for complete NGV adoption. However, a concerted effort from multiple agencies is necessary to realize this. The presence of different companies within the energy supply chain network makes it difficult to coordinate the locations of new gas refueling stations. Furthermore, the energy price is still heavily regulated, and setting the price would require cooperation with other government agencies outside the energy sector.

The free kit policy had the highest adoption rate among individual policies. The number of adopter agents resulting from this policy has a median value of 234.5 (234,500 cars), which is substantially higher than the baseline policy. Furthermore, more than 100 agents became adopters in 75% of the entire scenario ensemble. Note that the free kit policy stimulates the adoption in two ways. First, at the start of the simulation, there may be some agents who have already overcome multiple barriers (i.e., barriers presented in Figure 4) in the Evaluating state. These agents were grounded in the Potential state because they had not received the "message" from the adopter agents (see Transition 1 in Figure 3). The free kit policy increased the presence of adopter agents at the start of the simulation; hence, more "messages" were sent to agents in the Potential state. This helped other agents escape the Potential state and accelerated the entire adoption process. Second, this policy immediately relaxed the aggregated social–behavioral barrier within the complex barriers. Because this policy is the most successful individual policy, the social–behavioral barrier is the most dominant barrier in the current condition.

Individual policies targeting the structural and economic barriers were found to be less effective for improving the adoption rate. The implementation of the infrastructure enhancement policy would have incurred a total cost of approximately IDR 900 billion (~USD 63 million) to develop 60 additional NGV refueling stations (DetikFinance, 2012). Surprisingly, despite having the highest cost, this policy only delivered marginal improvement in the number of adopter agents with a median value of 76.5 (76,500 cars). These results show that, although the low availability of refueling stations is often blamed for hindering the adoption of NGV in Jakarta (Sulistyono & Sopha, 2013), infrastructure enhancement alone is insufficient for improving the situation. The kit subsidy policy performed even worse with only a marginal improvement from the baseline policy. Apparently, financial incentives are the least attractive measures. This result is supported by the fact that the converter kit price (IDR 17 million) is far lower than the purchasing price of cars in Jakarta (>IDR 150 million). Consequently, a minor reduction in the converter kit price would not significantly stimulate the car owners' willingness to adopt NGV. These results cumulatively strengthen the hypothesis that the social–behavioral barrier is the dominant one in the current situation (baseline policy).

Two additional observations can be made from the simulation results. First, to some extent, the number of agents in the Potential and Evaluating states are correlated with the number of agents in the Adopter state. The baseline, kit subsidy, and infrastructure enhancement policies yield similar median values for the number of agents in the Potential state. The distribution of these median values, however, is more spread out in the infrastructure enhancement policy, which indicates that in a larger number of scenarios, the infrastructure enhancement policy results in a smaller number of agents in the Potential state. This leads to the second observation which is related to the robustness of the policy. A narrower spread of distribution results indicates a more robust policy. Whether robustness is preferred depends on the context. For instance, the relatively narrow spread of results from the baseline and kit subsidy policy in Figure 5a is less desirable because the general preference of the problem is to have a low number of agents in the Potential state. Conversely, with respect to the total number of adopter agents in Figure 5c, a robust policy is preferred if the median value is high.

3.1 Identification of dominant barriers

Identification of the dominant adoption barrier in each policy alternative marks the vulnerability analysis phase of the EMBDA approach. Figure 6 shows the classification of the number of agents in the Evaluating state based on the adoption barriers they faced at the end of the simulation run. The nodes in the graph indicate the median value over 2000 scenarios, while the whiskers indicate the 25th and 75th percentile of the distribution. An agent might face more than one adoption barrier at a time. Such combinations of multiple adoption barriers are not presented because the focus of this phase is to identify individual dominant barriers rather than their combinations. Accordingly, for each policy in Figure 6, the total percentage might exceed 100%.

[Figure 6 here]

Figure 6 shows how the landscape of adoption barriers changes according to different actions taken. In the current situation (baseline policy), more than 80% of the agents face the social–behavioral barrier, followed by the economic and structural barriers with median values of 42% and 35% respectively. This result explains the success of the free kit policy in comparison to other individual policies. As the number of agents facing the social–behavioral barrier is twice the number of agents facing the other two barriers, confronting this barrier significantly increases the adoption rate. The kit subsidy policy marginally reduces the economic lag, although the overall landscape of adoption barriers remains similar to the baseline policy.

A substantial shift in the landscape of adoption barriers can be observed upon the implementation of the free kits, infrastructure enhancement, and integrated policies. The individual policies manage to reduce their targeted barriers. The free kit policy significantly reduces the number of agents facing the social–behavioral barrier, making this barrier the least important. Subsequent to implementing the infrastructure enhancement policy, only approximately 10% of agents still face the structural barrier. The integrated policy suppresses both the structural and social-behavioral barriers (with median values of 10% and 2%, respectively), while surprisingly the economic barrier prevails (with a median value of 67%). This result is counterintuitive because the converter kit price (IDR 17 million) is far lower than the prices of cars in Indonesia (> IDR 150 million). Thus, the economic barrier is not expected to strongly dominate other barriers.

3.2 Policy vulnerabilities

The final phase of the EMBDA approach attempts to identify policy vulnerabilities, i.e., scenarios in which a policy fails to meet its objective. In this study, we defined the objective of each policy as not falling above the 75th percentile of the dominant adoption barrier of that policy; consequently, there will be 500 undesired scenarios in each policy (25% of the total 2000 scenarios). The PRIM algorithm was applied to identify the high-density region within the uncertainty space that results in undesired scenarios.

Figure 7 presents the algorithm results. Lists of uncertain variables that define undesired scenarios in each policy are presented, along with the bandwidth of the variables. The left- and right-most values in each subfigure are the entire plausible range of the variables, as defined in Table 1. The blue lines depict the bandwidths of the uncertain variables where the policy tends to fail, while the numbers in blue depict the exact threshold values of the bandwidths. These bandwidths define the narrative of the undesired scenarios. For instance, based on the results in Figure 7b, the free kit policy fails under the following conditions: the converter kit price exceeds IDR 14 million, the price reduction of the annual converter kit is below 2.1% per year, and the oil fuel price exceeds IDR 6500 per liter.

[Figure 7 here]

Figure 7a shows that the kits subsidy tends to fail under the following condition: the gas fuel price is higher than IDR 3100 per liter, the oil fuel price is less than IDR 8100 per liter, the converter kit price is more than IDR 14 million per liter, and the contact rate of the adopter to the other agents is higher than 39 days. This result is in agreement with conventional logic because a higher gas price and lower oil price would reduce the potential relative savings accumulated by using NGV, thus making it less attractive. Furthermore, a higher converter kit price would make adoption less affordable and longer durations in between messages from adopter agents would make fewer potential agents move to the Aware state.

The undesired scenarios for the infrastructure enhancement policy presented in Figure 7c also have a trend similar to the kit subsidy policy. A noticeable difference is the threshold of the oil price, which is far lower than the threshold in the undesired scenarios of the kit subsidy policy. This indicates that the oil price influences the success of the infrastructure enhancement policy to a greater extent than the kit subsidy policy. Conversely, identified bandwidths for undesired scenarios in the free kit policy and the integrated policy are more counterintuitive (Figure 7b and Figure 7d). Here, a higher oil price tends to result in policy failure.

4 Conclusion and Policy Implications

The results of this study demonstrate that the importance of NGV adoption barriers changes upon implementation of different policies. The most critical uncertainty was found to change depending on the policy implemented. The identification of the dominant adoption barrier *a posteriori* the implementation of the policy can be useful for policy analysis in two ways. First, the results can provide contextual insight on formulating additional measures, additional to each individual policy, which would be most useful for advancing the adoption. For example, as the economic barrier dominates after implementation of either the integrated or the free kit policy, policymakers can focus on additional policies that target this particular barrier. Policies that aim to reduce the converter kit price or target the affordability threshold of car owners are particularly useful in this case.

Second, the results can help policymakers in prioritizing their budget to increase their understanding of the identified dominant barrier, e.g., by conducting further studies. For example, Figure 6 shows that, under the current situation (the baseline policy), the structural barrier is the weakest one. Hence, funneling budgets to identify the appropriate locations for constructing new NGV refueling stations or coordinating between different institutions to realize their construction is not an effective approach to increase the NGV transition. Moreover, studies that investigate the specific social-behavioral barriers that are prevalent among potential NGV adopters would be more valuable. With respect to the other policies (policy 2 to policy 5), a better understanding of the dominant barrier would help in developing additional measures discussed in the previous paragraph.

Our results further suggest that uncertainties identified by the vulnerability analysis should be monitored by the policymakers. In the future, if uncertain variables unfold to the bandwidths identified in this study (see Figure 7), additional measures should be taken to safeguard the potential success of the policy. The vulnerability analysis identifies different uncertain variables as the primary cause of policy failures. As different uncertain variables are affected by different institutions, to safeguard the success of the policy, a concerted collaboration between multiple institutions is a prerequisite.

The collaboration between institutions depends on the identified uncertain and influential variables. To this end, the oil fuel price appears as a critical uncertainty in all policies. The oil price is subject to government regulation, prompted by the Ministry of Energy and Mineral Resources (MERM). However, to determine the appropriate oil price, the MERM has to also coordinate with the Ministry of Finance and the state-owned oil and gas companies (i.e., PERTAMINA and PGN). The oil fuel price is not the only uncertain factor that is highly influential. In Figure 7a to 7c, the scenario discovery results from the individual policy show that the converter price is likewise a decisive uncertain variable. To drive this variable to the intended direction, the MERM has to cooperate with the Ministry of Industry (MoI). The MoI could encourage automotive industries to supply the converter kit as part of their built-in feature offer to the consumer. Further, for policies wherein contact rate is part of the discovered vulnerabilities, a medium to long-term campaign to increase public awareness should be implemented. This could be realized through a public campaign in social media or at all vehicle refueling stations. The NGV community can likewise help by supporting such campaigns.

In summary, this study has identified the dominant adoption barriers and the vulnerabilities of alternative policies of NGV adoption in Jakarta. The economic barrier appears as the most prevalent barrier when executing all policies, dominating over the structural and social-behavioral barriers. Meanwhile, the social-behavioral barrier appears as the most dominant factor under the current condition. Among the four alternative policies (kit subsidy, free kit, infrastructure enhancement, and integrated policy), two have similar trends concerning their vulnerabilities, namely the kit subsidy policy, and the infrastructure enhancement policy. Both of these policies tend to fail if the oil fuel price is not too high, and the prices of gas fuel and converter kits are not too low. On the contrary, the free kit policy and the integrated policy tend to fail if the oil fuel price is low. The kit subsidy policy and the infrastructure enhancement policy require a constant stream of government expenditure throughout a period of time, while the cost of the free kit policy is only incurred once at the beginning of the execution.

Furthermore, the proposed approach could be useful for future agent-based adoption policy analysis studies. The EMBDA approach demonstrated in this study tailors the generic EMA framework for a model-based adoption study by including the adoption barrier component. The approach proves to enable the evaluation of the consequences and vulnerabilities of alternative policies under deep uncertainties through a computational experiment of a large number of simulations. The approach enhances the explanatory power of agent-based modeling by exploring not only the performance alternative policies but also their vulnerabilities.

In future research, we recommend addressing the following issues that pose limitations in this study. This study did not take into account the behavioral or nudge effect of the infrastructure enhancement policy. Whereas this study only considers the total number of adopter agents, a cost-benefit analysis of policies could also be conducted to provide a more detailed result. The cost structure of the policy is of central concern. For instance, the kit subsidy policy and the infrastructure enhancement policy require a constant stream of government expenditure throughout a period of time. In contrast, the cost of implementing the free kit subsidy is incurred only once at the beginning of the policy execution. Moreover, the timing of different policies was not evaluated in this study. Although this is not within the scope of this study, this issue should likewise be addressed, e.g., by borrowing the concept from the adaptation pathways.

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Appendix A

See Table A1

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Table(s)

Table 1 Uncertain variables and their parameter range

Variable	Base value	Minimum value	Maximum value
Gas fuel price	IDR 3100 / liter	IDR 2500 / liter	IDR 5000 / liter
Oil fuel price	IDR 7000 / liter	IDR 5000 / liter	IDR 9000 / liter
Converter kit price	IDR 17 million	IDR 12 million	IDR 25 million
Contact rate	60 days	30 days	90 days
Annual kits price reduction	2%	0.5%	2.5%
Minimum affordability threshold	7.5%	5%	10%
Maximum affordability threshold	12.5%	12%	15%
Minimum distance threshold	4.5 km	3 km	6 km
Maximum distance threshold	9 km	7 km	12 km

Table A.1. ODD+D description of the agent-based model based on the template provided in Müller et al. (2013).

Outline		Guiding questions	Description
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	This study evaluates the policy performance of pushing the adoption of Natural Gas Vehicles in Indonesia. The study proceeds by exploring the changes in the relative importance of different adoption barriers, and by identifying the vulnerability of policies, i.e., the scenarios leading to policy failures. The developed model will assist policy makers in systems understanding and quantitative prediction, thereby improving their NGV-adoption policies.
		I.ii.b for whom is the model designed?	Scientists, students, teachers, modelers, NGV policy makers

	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	Agent-based model layer - Vehicle owners in Jakarta Infrastructure layer - NGV refueling stations
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	Vehicle owners - Stages of NGV adoption: Potential, Aware, Evaluating, Deciding, and Adopter - Attributes related to structural barriers of adoption o Home location o Work location o Closest NGV refueling station o Distance threshold - Attributes related to economic barriers of adoption o Income o Expected break-even point o Affordability threshold - Attributes related to social–behavioral barriers of adoption o Social network: (i) agents within the same home location, (ii) agents within the same work location, and (iii) several other random agents in the model (small-world network) o Innovativeness of adopting the new technology o Contact rate with social network o Social threshold NGV refueling stations - Location
		I.ii.c What are the exogenous factors/drivers of the model?	- Gas fuel price - Oil fuel price - Converter kit price - Annual kits price reduction
		I.ii.d If applicable, how is space included in the model?	- Vehicle owners are spatially distributed among the 42 districts in Jakarta - NGV refueling stations are spatially distributed based on the existing infrastructure - The closest refueling station to a vehicle owner agent is calculated using the Euclidean distance

		I.ii.e What are the temporal and spatial resolutions and extents of the model?	- The simulation time horizon ranges from 2017 to 2030 - The spatial extent is the entire Jakarta province. Distance is the Euclidean distance (not considering the real road network)

	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	The simulation environment of the model enables a continuous time step. In the model, agents perform actions on a daily basis, depending on their current adoption state.
			- Vehicle owners in the ‘Potential’ state
			  o Behavioral barrier: wait for “message” triggers from the ‘Adopter’ agents in their social network
			  o Move to the ‘Aware’ state after receiving a “message”
			
			- Vehicle owners in the ‘Aware’ state
			  o Economic barrier: wait for certain months before moving to the ‘Evaluating’ state. The waiting time depends on the ratio between the oil fuel price and the gas fuel price
			
			- Vehicle owners in the ‘Evaluating’ state
			  o Agents evaluate the following three barriers every four months:
			    ▪ Social–behavioral barrier: To overcome this barrier, the percentage of ‘Adopters’ in an agent’s social network should exceed the social threshold of the agent.
			    ▪ Economic barrier: To overcome this barrier, the ratio of the converter kit price to the agent’s annual income should be lower than the affordability threshold of the agent.
			    ▪ Structural barrier: To overcome this barrier, the distance between the agent’s home/work location and the closest refueling station should be lower than the distance threshold of the agent.
			  o If agents manage to overcome those barriers, they move to the ‘Deciding’ state
			
			- Vehicle owners in the ‘Deciding’ state
			  o Economic barrier: The agent waits for several months before moving to the ‘Adopter’ state. The waiting time depends on the expected break-even point of investing in the NGV converter kit

			- Vehicle owners in the 'Adopter' state o Agent sends a "message" randomly to one agent within its social network. The rate of this message-sending activity depends on the agent's contact rate Aside from the above state-dependent activities, the price of the converter kit yearly decreases, at the annual kit- price reduction rate.
II) Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	The heterogeneity of vehicle owners is based on the diffusion of innovation theory (Robertson, 1967; Rogers, 2010). The overall emerging behavior of the transition and diffusion phenomenon follows the literature of the bass diffusion model (Bass, 1969; Rahmandad & Sterman, 2008), which should yield an S-shaped adoption curve.
		II.i.b On what assumptions is/are the agents' decision model(s) based?	The agents' decision model is grounded on two theories. First, is the five-stage adoption process in the diffusion of innovation theory (Rogers, 2010). Second is the barriers along these adoption stages, which are based on a review paper on the adoption of energy-efficient technologies (Hesselink & Chappin, 2019). The paper finds three categories of barriers: economic, structural, and social–behavioral.
		II.i.c Why is a/are certain decision model(s) chosen?	- Previous studies on NGV transition in Jakarta focused on adoption using a single-stage utility-based approach (Sopha et al., 2017; Sulistyono & Sopha, 2013). We want to extend the previous studies to multi-stage adoption logic. - There is no clear demarcation of the adoption barriers in previous studies. - The relationships among the adoption barriers, the agents' attributes, and the policies implemented by the government need to be clarified. This clarification is central to the Exploratory Model-based Diffusion Analysis (EMBDA) approach.
		II.i.d If the model / a submodel (e.g. the decision model) is	- Socioeconomic statistics were primarily derived from the official statistics of Jakarta (Pardosi et al., 2017).

		based on empirical data, where does the data come from?	- Travel behavior data were derived from large-scale transport surveys in Jakarta (JUTPI, 2012; SITRAMP, 2004; Sugiarto et al., 2014)
		II.i.e At which level of aggregation were the data available?	Mainly at the district and provincial levels. The parameterization of the agents' attributes were randomly sampled from these aggregated data.
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?	Decision-making activities are performed at the agents' (in this case, vehicle owners) level. Depending on its current adoption state, each agent performs different activities as explained in I.iii.a
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	From a social planner's point of view, the agents are expected to arrive at the 'Adopter' state of adoption. The agents, however, must first undergo the four states of adoption: Potential, Aware, Evaluating, and Deciding. When transitioning from one state of adoption to the next, the agent must overcome different adoption barriers.
		II.ii.c How do agents make their decisions?	- Decision tree (from 'Potential' to 'Aware', and from 'Evaluating' to 'Deciding') - Delay function (from 'Aware' to 'Evaluating', and from 'Deciding' to 'Adopter')
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	There are no dynamics within the decision-making logic of the agents. However, agents in the 'Evaluating' state regularly observe their environment and move to the 'Deciding' state when all barriers are overcome. The annual reduction of the converter kit price may remove the economic barrier.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	Not directly, however certain attributes of the agents—contact rate, social threshold, and innovativeness—reflect the local social norms.
		II.ii.f Do spatial aspects play a role in the decision process?	Yes, the structural barrier of the adoption process requires agents to evaluate the distance of the closest refueling station to their home and work locations.

		II.ii.g Do temporal aspects play a role in the decision process?	N/A
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Uncertainty is not explicitly considered in the decision-making process.
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	N/A
		II.iii.b Is collective learning implemented in the model?	N/A
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	From the social–behavioral barrier viewpoint, vehicle owners judge the social acceptability of NGV from the adoption behavior of their social network. From the economic barrier viewpoint, vehicle owners consider the expected profitability of purchasing converter kits based on the potential saving of their annual fuel expenditure and the converter kit price.
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Agents observe the adoption state of other agents in their social network. A high percentage of 'adopters' in an agent's social network is important for overcoming the social–behavioral barrier.
		II.iv.c What is the spatial scale of sensing?	The social network of the agents.
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Agents are assumed to know these variables.

		II.iv.e Are costs for cognition and costs for gathering information included in the model?	N/A
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	N/A
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	Vehicle owners calculate the expected break-even point of purchasing a converter kit. The revenue in their calculation is the expected annual savings from reducing their fuel expenditure. However, agents do not consider the future changes in fuel price nor the discounts conferred by benefits.
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Technically no, however, realistically yes as oil and gas prices will change
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Direct interactions: agents in the 'Adopter' state periodically send a "message" to another agent in their social network
		II.vi.b On what do the interactions depend?	Social network of the agents
		II.vi.c If the interactions involve communication, how are such communications represented?	Agents in the 'Adopter' state periodically send a "message" to another agent in their social network
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	N/A
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that	Agents form their own social networks randomly at the beginning of the simulation. The social network of each agent is assumed static during the entire simulation period.

		affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	As previously mentioned, the number of agents in the ‘Adopter’ state in a social network is related to the social–behavioral barrier of the agents within that network.
		II.vii.b How are collectives represented?	N/A
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	The heterogeneity of the agents’ attributes is explained in I.ii.b.
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	The heterogeneity of the agents’ activities based on their adoption states is explained in I.iii.a.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	- Transition from the ‘Aware’ to the ‘Evaluating’ state is hindered by an economic barrier that stochastically delays the transition process. - Transition from the ‘Deciding’ to the ‘Adopter’ state is also hindered by an economic barrier that stochastically delays the transition process. - The rate at which ‘Adopter’ agents send “messages” to their social network is internally stochastic and depends on the contact rate attribute of the agent. - The agent who receives the “message” is also randomly chosen from the social network.
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	The ABM collects the following data: - Number of agents within each adoption state (Potential, Aware, Evaluating, Deciding, Adopter) at the end of the simulation run - Percentages of agents in the ‘Evaluating’ state facing each adaption barrier (Economic, Structural, Social-behavioral, see I.iii.a)

		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	The key results include the numbers of adopters at different stages of adoption. The rates of different stages of technology adoption are assumed as responses to policy changes that push the adoption of NGVs in Indonesia.
III) Details	II.i Implementation Details	III.i.a How has the model been implemented?	The model is implemented in the Licensed Anylogic 7.0.2 Professional simulation suite owned by Systems Engineering, Modeling, and Simulation (SEMS) Laboratory, Universitas Indonesia
		III.i.b Is the model accessible and if so where?	N/A
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	An agent represents 1000 vehicle owners in Jakarta. Thus, at the initial state, we generated 3480 agents. The agents were spatially distributed across the 42 districts. The percentage of agents in each district corresponded to the population of that district relative to the populations in all other districts. Other socioeconomic and behavioral attributes of the agents were randomly sampled from the official statistics and the travel surveys. We assume that all agents begin in the 'Potential' state. However, as there are around 7000 existing NGVs, seven random agents start in the 'Adopter' state.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	The initialization is the same in all computational experiments.

		III.ii.c Are the initial values chosen arbitrarily or based on data?	- Home location: allocated statistically based on the population data (Pardosi et al., 2017)
			- Work location: allocated randomly across the 16 business and industrial districts in the Greater Jakarta Region (JUTPI, 2012; SITRAMP, 2004)
			- Distance threshold: based on surveys by JUTPI (2012) and SITRAMP (2004)
			- Income: allocated statistically based on socioeconomic statistics (Pardosi et al., 2017)
			- Affordability threshold: statistically inferred by interpolating between the median annual household income and expenditure statistics (Pardosi et al., 2017)
			- Social network: randomly formed
			- Innovativeness: follows the standard distribution proposed by Robertson (1967): Innovators (2.5%), Early adopters (13.5%), Early majority (34%), Late majority (34%), Laggards (16%)
			- Contact rate: assumed as 30 days
			- Converter kit price, gas fuel price, oil fuel price: based on actual prices.
			- Social threshold: dependent on the Innovativeness attribute.
			  o Innovators: triangular (0, 1%, 3%)
			  o Early adopters: triangular (0, 3%, 7.5%)
			  o Early majority: triangular (3%, 7.5%, 15%)
			  o Late majority: triangular (7.5%, 15%, 25%)
			  o Laggards: triangular (10%, 25%, 40%)
			- Converter kit price, gas fuel price, oil fuel price: based on actual prices
			- Annual kit price reduction: assumed as 2%.

	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	N/A
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	N/A
		III.iv.b What are the model parameters, their dimensions and reference values?	See Table 1 of the main text

		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	N/A

Figure(s)

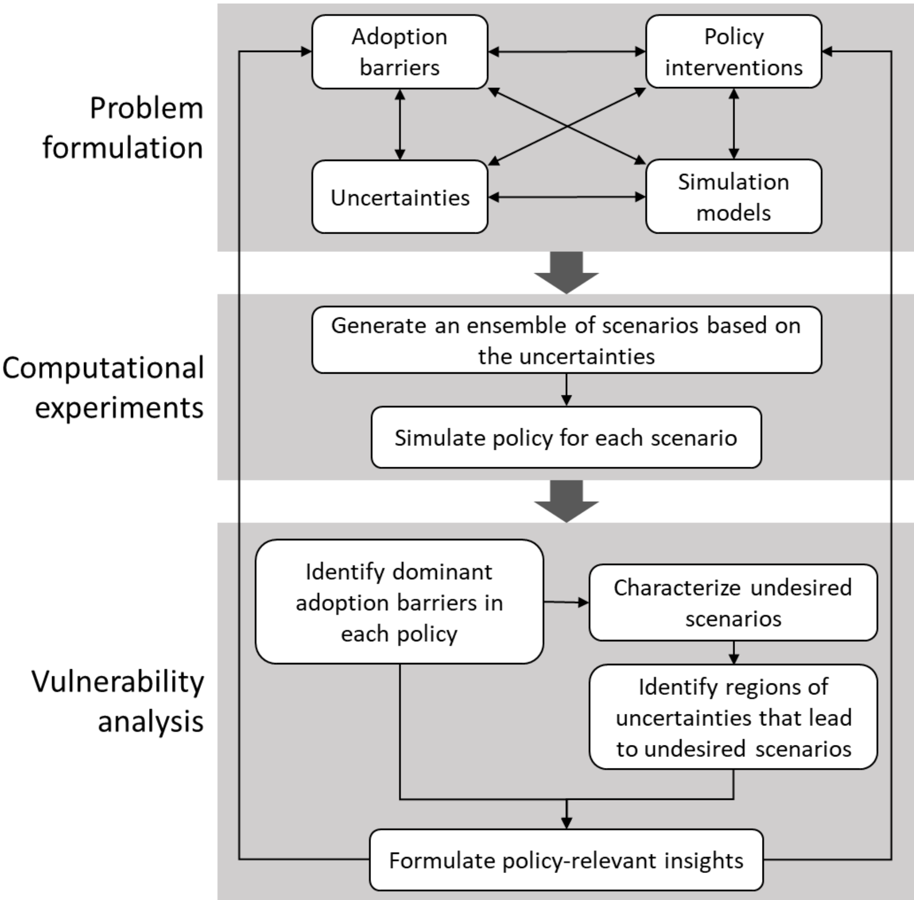

Fig. 1 Stages of the EMBDA approach

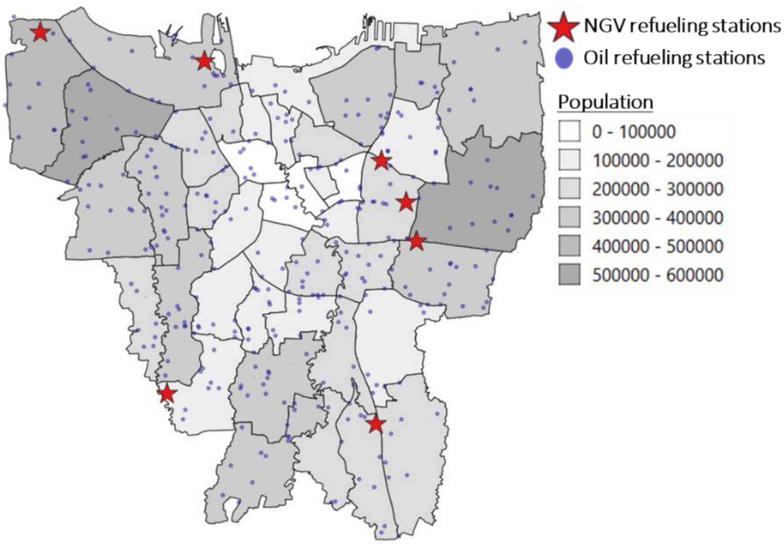

Fig. 2 Population of districts and locations of refueling stations in Jakarta

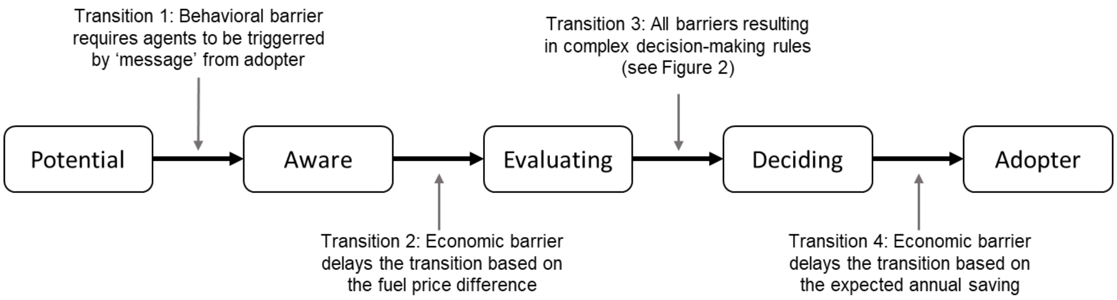

Fig. 3 Chart of agent states and transitions

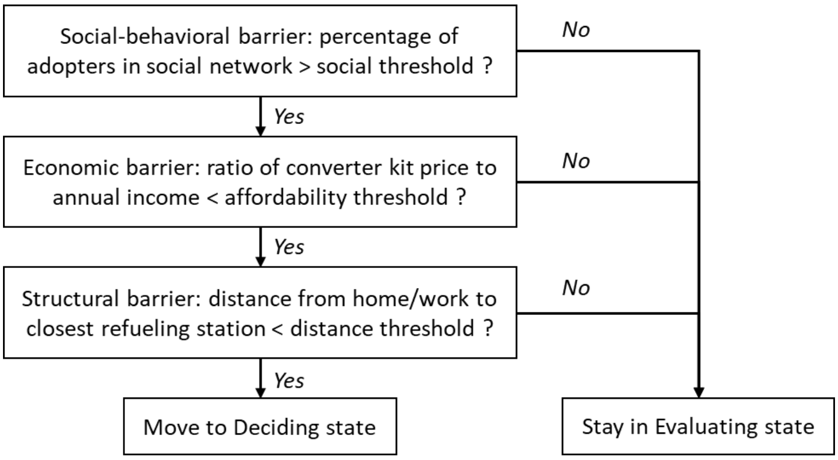

Fig. 4 Decision-making logic of Transition 3

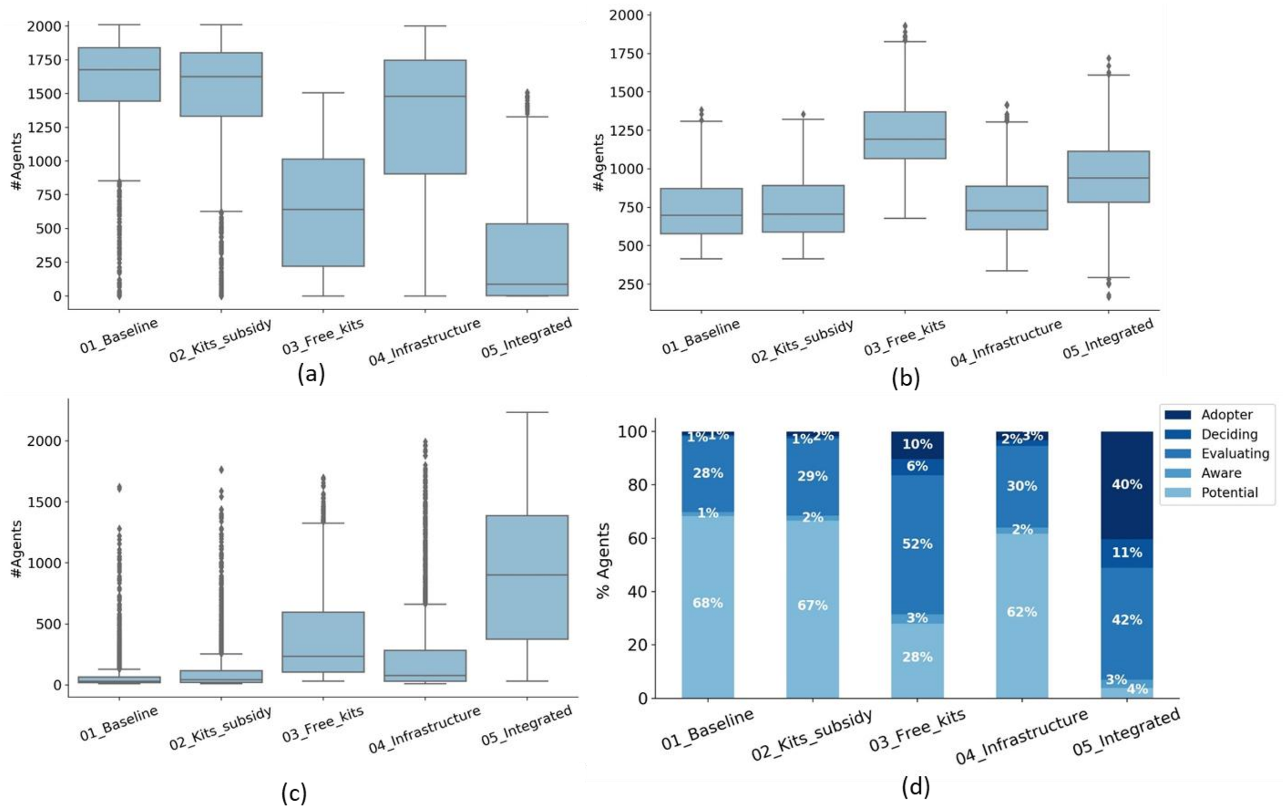

Fig. 5 Numbers of agents (a) in the Potential state, (b) the Evaluating state, (c) the Adopter state, (d) in each adoption state calculated as a percentage, obtained by simulation.

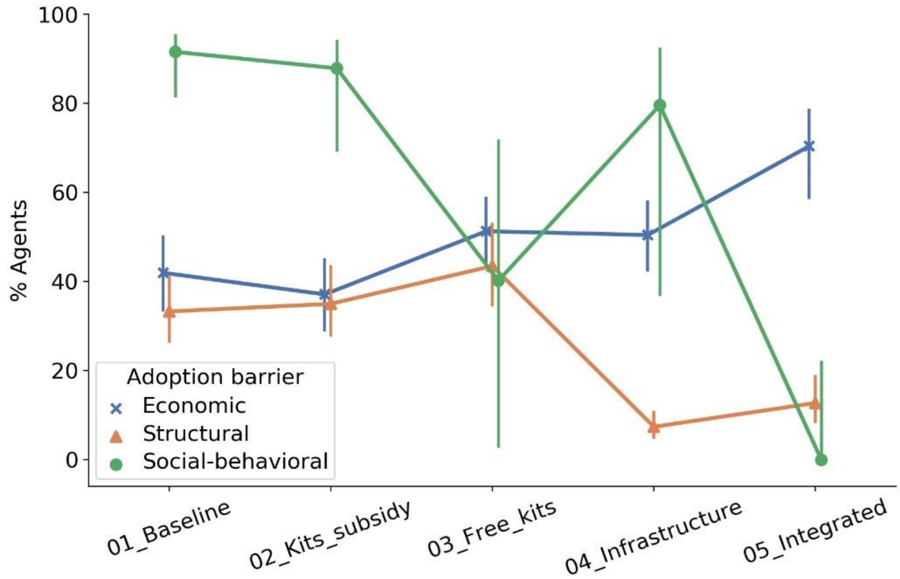

Fig.6 Percentage of agents in the Evaluating state facing each adoption barrier

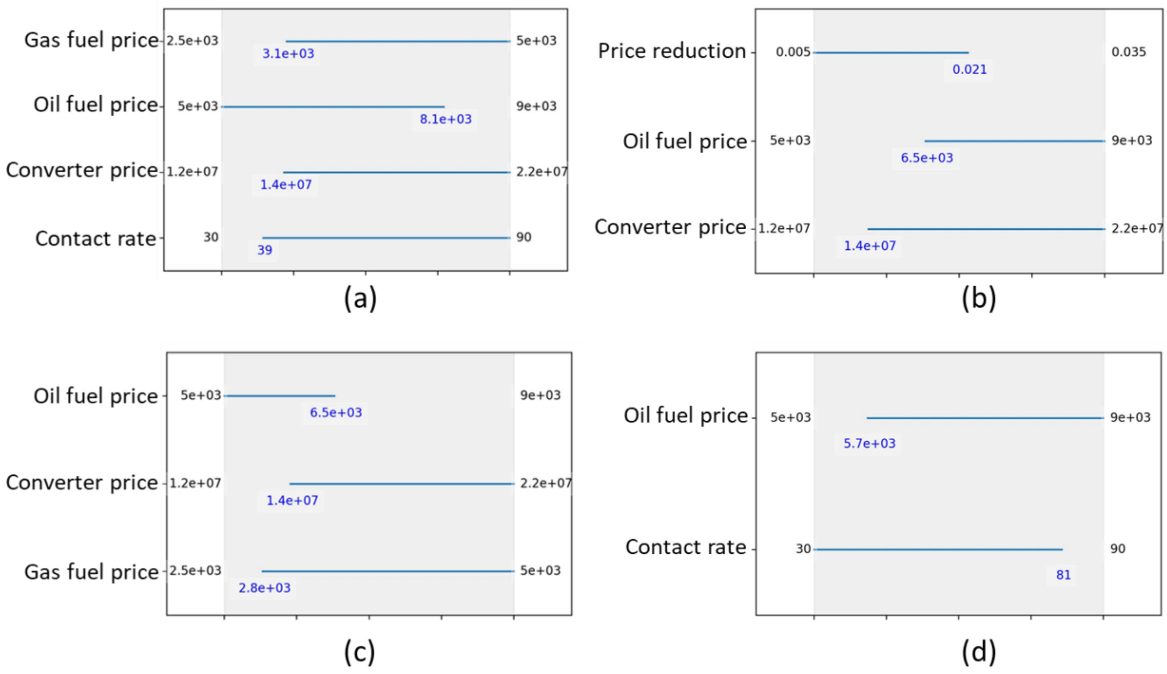

Fig. 7 PRIM algorithm results for (a) kit subsidy policy, (b) free kit policy, (c) infrastructure enhancement policy, and (d) integrated policy