Targeting incentives to adopt wind-assisted technologies in shipping by agent-based simulations

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Abstract

Although the maritime industry has introduced technological improvements, shipping activity is still a major contributor to greenhouse gas emissions. Using more intelligent incentive policies, such as subsidies, seems a way to increase green technology adoption. Our proposal is to engineer micro-level incentives to target a reduced set of adopters to optimize subsidies while encouraging adoption by shipowners. We focus on wind-assisted propulsion technology in shipping and test the effectiveness of targeting using agent-based simulations. The agent-based model employs a three-phase process, influenced by awareness of technology, economic factors, and networking. Experiments under different scenarios robustly analyze targeting policies and their impact on adoption rates. Our findings reveal that targeted incentives significantly improve adoption compared to a uniform distribution. The most effective targeting policies are those that select receptors based on their social activity and energy consumption, although the available budget affects the selection of criteria.

Keywords: Green technology; Targeting strategies; Maritime industry; Agent-based modeling; Adoption of innovations

1. Introduction

Shipping firms are increasingly addressing their ecological footprint by following government policy actions in response to climate change and shipping pollution and, indirectly, through the technological-push factor from new cleaner fuels and on-board energy saving improvements (Lindstad et al., 2023; Zhou et al., 2023). Shipping activity has a significant environmental impact both through its contribution to climate change through greenhouse gas (GHG) emissions and its release of air pollutants such as nitrogen oxides (NO_x) and sulfur oxides (SO_x), which negatively affect air quality. Although the shipping industry has introduced incremental technological improvements in alternative fuels, hybrid power systems, and operational measures to tackle air pollution, scale-up costs and production limitations hinder large-scale adoption. Hybrid systems that combine renewable solar and wind energy provide a greater reduction in emissions, but are still in the early stages of development (Huang and Duan, 2023). Recent studies question the impact of regulatory frameworks due to their financial complexities, suggesting the need for intelligent financial engineering solutions and microlevel incentives tailored to specific shipping firms or ships (Schinas, 2022; Chica et al., 2023).

There is a strong link between the need for decarbonization in the shipping industry and the need to identify viable solutions for fuels and energy-saving technologies. This study is dedicated to the adoption of wind-assisted propulsion technology (WPT). Recent studies have challenged the current bias towards low-carbon and zero-carbon emission fuels in favor of WPTs and the potential gains that can be achieved through the combination of research with appropriate routing and voyage planning tools (Mason et al., 2023a,b). The focus on WPT in this study is in line with previous articles resulting from the Interreg-funded WASP project (NSR Interreg, 2024; Chica et al., 2023; Ghorbani et al., 2024), which ensures data availability and a comprehensive understanding of all aspects related to WPTs

Although the existing literature has extensively analyzed market-based mechanisms to

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decarbonize shipping, the role of public incentives, such as subsidies, requires more attention. Zhang et al. (2024) demonstrated that institutional subsidies are essential for hydrogen bunkering and retrofitting ships for hydrogen propulsion, showing that subsidies balance market dynamics until they are no longer needed. Subsidies in the shipping industry increase profits and social welfare through reductions of environmental impacts and can stabilize market dynamics compared to cap-and-trade regulations (Huang et al., 2023). However, the question of how to better target the recipients of subsidies to enhance the efficacy of promoting green technologies remains unanswered and appears to be an appropriate tool for a wiser distribution of subsidies.

To address this knowledge gap, the research question in this article is: *How can green technology adoption incentives be used more efficiently?*. Our main proposal is to solve this problem by selecting target beneficiaries of subsidies within a heterogeneous population of possible adopters. Therefore, instead of uniformly distributing incentives among all shipowners, we propose to wisely allocate incentives to optimize the use of resources and their impact. The way of selecting shipowners for institutional incentives is public and clear for all agents but conditioned by the characteristics of their vessels to ensure appropriate targeting. Thus, the focus of the model is the application of micro-targeting policies (Ramkumar et al., 2022) to a reduced set of possible adopters that obtain subsidies for their installation costs, which are one of the most important adoption barriers for WPT.

We use agent-based modeling (ABM) (Bonabeau, 2002; Eppstein et al., 2011) to simulate how WPT is adopted after applying the targeting policies. ABM is a bottom-up simulation technique for modeling complex systems through a population of agents. Its key advantage in the adoption of green technology is the ability to facilitate a dynamic bottom-up structure from which global behavior emerges. Interactions among agents is another key aspect of ABM to better simulate the adoption of green technology. For instance, ABM facilitates the inclusion of networking activities as a way to increase awareness of technology and its knowledge, given its importance when adopting green technologies (Jansson et al., 2017).

The use of ABM contributes to the evolution of the adoption of WPT over time and the results of the implementation of different policies and incentive strategies, as previously shown in the maritime industry (Bas et al., 2017; Holmgren et al., 2014) or in previous studies on the adoption of green technology (Karslen et al., 2019; Rai and Robinson, 2015). Our proposal aims to extend the previous designs (Chica et al., 2023) by incorporating a way to target incentive policies to a limited set of key or seed agents. The decision to adopt or not makes use of a utility that takes into account social and economic drivers by defining a modulating factor, but a possible adopter needs to previously have awareness of the technology. We design various incentive policies by considering different attributes of the vessel to identify seed agents to be targeted. This set of attributes includes factors such as the age of the vessels, their energy consumption, and their social influence.

Through ABM simulations, different targeting strategies are analyzed to understand which outperform the rest and the targeting incentives are compared with respect to the general incentives to all vessels. The study also considers how well targeting policies work in different scenarios, including variations in fuel prices, networking, sailing distances, subsidies, and the percentage of targeted vessels. The potential impacts of these scenarios are analyzed to observe how model output varies when changing the value of a single input parameter while all other parameters remain unchanged. Then, a complete simulation-based analysis will provide a deeper understanding of how targeting policies behave when adopting WPT under different policies and scenarios by enhancing the model understanding by stakeholders.

This work is organized as follows. First, Section 2 provides a review of the literature and background on WPT, subsidies in the maritime industry, and ABM. Section 3 describes the proposed computational model and Section 4 specifies the data and parameters used for the experiments. Section 5 shows the main results and analyzes them. Section 6 discusses the theoretical, practical, and methodological implications of the work. Finally, Section 7 summarizes the main findings and suggests directions for future research.

2. Literature review

We first highlight WPT as our technological focus in Section 2.1. We review public subsidies to promote green technologies in shipping in Section 2.2. Finally, related works on the use of ABM for green technologies and in the maritime industry are summarized in Section 2.3.

2.1. Wind-assisted propulsion technology (WPT)

According to Clarksons Research (2024), there are still few vessels equipped with WPTs (fleet and orderbook), including approximately 40 with Flettner rotors, 43 with suction wings, 18 with rigid sails and 4 with wind kites. Along with other energy saving technologies, such as air lubrication hull systems or improved propellers, the deployment of WPT is expected to increase in the coming years (Clarksons Research, 2024). Recent research about the links between shipping decarbonization and the uptake of WPT indicates the importance of previous policy upgrades such as the carbon intensity indicator (CII). It is expected, for example, that the CII will lead to more and more companies installing technologies such as WPT and solutions such as voyage optimization. Some studies indicate carbon savings of up to 18% with WPTs if used in combination with, for example, voyage optimization solutions and slow steaming. In addition, WPTs have a long-term reduction potential if considered as hybrid solutions (Mason et al., 2023a).

Another recent study highlights the potential for the adoption of WPT or hybrid systems in the context of large developing countries like Bangladesh (Munim et al., 2023). The authors point out the potential of WPT to contribute to decarbonization pathways in its hybrid form (liquefied natural gas -LNG- and heavy fuel oil -HFO- hybrid systems), as the technology meets expert criteria for its further adoption in terms of capital costs, fuel price and operating costs. Furthermore, the authors highlight the versatility and advantages of WPT, in terms of adaptation to the conditions of developing economies, compared to competing technologies such as battery-electric power or biodiesel, which require higher investment in power generation or bunkering (Munim et al., 2023). A few studies have previously analyzed WPT in terms of fuel savings. One paper, using data from the Interreg WASP project, analyzed experimental data (strain gauge measurements) with modeling to understand fuel savings under different weather conditions, and with slow steaming and port stops. The project showed a correlation between wind speed and fuel savings (a 5%

increase in wind speed equates to an approximate 12% increase in fuel savings). Similarly, slow steaming can increase fuel savings when the ship has WPT technology installed (nearly 16% fuel reduction as long as the ship's speed is reduced) (Ghorbani et al., 2024).

Other studies have made use of computational simulation methods, basing their research on a single ship. For example, Mason et al. (2023a) used a model called Pelican to simulate the effects of four Flettner rotors on the energy savings gains of a single ship (specifically, a $80,000$ DWT Panamax bulk carrier). The study analyzes the impacts of wind on the drag, lift and heel of the ship, which are connected to the effects of the Flettner rotor. The main contribution of the article is that it demonstrates that extremely high fuel savings can be achieved (up to 44%) if weather route planning is used in advance to optimize the trip using continuously updated weather forecasting. The conclusions reached in the study are similar to those reported by Ghorbani et al. (2024). According to the latter study, voyage optimization techniques can lead to relatively important fuel savings of up to 30% on routes in specific corridors with favorable wind conditions when using wind propulsion and hybrid wind propulsion systems, contributing significantly to carbon emission reductions of up to 60%.

In the present paper, the case study uses the VentiFoil technology of Econowind, supplier to the Interreg WASP project (ECONOWIND, 2024), which is a rigid wing solution. Suction wings such as VentiFoil generate a lift similar to the effect of airplanes by introducing internal fans and ventilated wings. As part of the Interreg WASP project, Ghorbani et al. (2024) used data and modeling of experimental sailing conditions to understand the effect of rigid sails on energy savings. The study focused on a container vessel equipped with two VentiFoil units whose route spanned different locations in the North and Baltic Seas.

2.2. Subsidies as a policy of boosting green technologies in shipping

Zhang et al. (2024) developed a methodology to optimize subsidies for hydrogen fuel deployment in Chinese ports / shipping companies. Based on the simulation results of their study, the authors claim that state subsidies could be a public policy with two-way outcomes, contributing to reaching the government target of zero to low carbon emissions. The paper addressed ships' retrofitting for hydrogen propulsion installation, concluding that the initial uptake of bunkering facilities and retrofit cannot be done without governmental subsidies. In their study, they model the number of ports that build bunker infrastructure against sales (hydrogen sold to ships). They also conclude that, under complex market dynamics involving two key actors (hydrogen-driven ships and ports), the likelihood of increasing sales and market demand change tend to balance each other until reaching an equilibrium when the subsidies are no longer needed.

Although most of the reviewed studies analyze a single type of incentive, Huang et al. (2023) analyzed the impact of government subsidies on technologies and services, focusing on the low-carbon maritime supply chain. This study reveals that both types of subsidies improve expected profits, greenness, and social welfare. However, technological investments significantly improve these aspects, stabilize the system, and return chaotic systems to a stable state. Furthermore, when considering cap-and-trade regulation, the carbon emission quota for the port does not affect optimal decisions, and an increase in carbon price promotes higher levels of carbon abatement. Interestingly, the impact of carbon price on port profits is indirectly related to the carbon quota. When the carbon emission quota is high, only the expected profits of the port increase with the carbon price, whereas the anticipated profits of all stakeholders decrease as the carbon price increases (Huang et al., 2023).

Given the focus at the supply chain level and not on the focal companies, the study of Huang et al. (2023) provides good insight into what happens to the shipping system when subsidies interact with other policies in place, thus providing some hints of common concerns at the system level. One critical insight has to do with the effects on the pricing of service provision: the researchers conclude that excessive subsidies towards carbon abatement technologies can lead to chaos in the pricing system. Since this research aimed to analyze the effect of low carbon technology subsidies on the supply chain, they conclude that to avoid a chaotic impact on the pricing system, it is the responsibility of the ports' actors to oversee the pricing of the carbon market. However, the government must establish carbon abatement technologies as a way to stabilize the market dynamics. Furthermore, with the increasing influence of freight forwarders, government subsidies have become more beneficial. Although government-set carbon quota do not affect optimal decisions when the pricing system is chaotic, maintaining carbon prices within a set range through macro-control can stabilize the system (Huang et al., 2023).

Methodologically, we build on the approach of a previous study (Chica et al., 2023) which used ABM to examine the impact of subsidies, carbon tax and social network interactions on promoting the adoption of WPTs. Although our study has a common focus on subsidies and incentives, other research approaches, such as that of Huang et al. (2023), take a different methodological path employing evolutionary game theory. Huang et al. (2023) explore cost-sharing mechanisms between ports and shipping companies to implement low carbon emission technologies, with a particular emphasis on supply chains and the decarbonization efforts of freight forwarders. This contrasts with our focus on direct incentives and adoption behaviors. By highlighting these different perspectives, we aim to demonstrate that while both studies address green maritime technologies, our approach provides unique insights into policy-driven adoption processes.

In another relevant study, Wang et al. (2022) use a Stackelberg game to model interactions between the government, a port, and multiple ships to optimize the efficiency of the subsidies, defined as the environmental benefit per monetary unit of the subsidies. The government, acting as the leader, provides financial support and influences the port operator, who sets the sale price of shoreside electricity based on these subsidies. The owners decide then whether to equip their ships with this technology and each participant decision is interdependent, with the government's subsidy policy affecting the port's technology price and, consequently, shipowners' decisions. The study emphasizes the focus on municipal-level subsidies. The subsidy structure includes two levels: subsidies for port operations and subsidies for ships. The model aims to maximize overall benefits by depicting and optimizing each participant's decision-making process. In terms of findings, Wang et al. (2022) show that when the total subsidy is less than $1,440,000$\$, the port incurs losses due to the gap between the price of the network and the price of sale. Above this amount, the port's utility stabilizes until the subsidy exceeds $1,440,000$\$. The utility of ships is more influenced by subsidies than by prices of shore side electricity (SSE), showing a trend similar to that of operational subsidies. Subsidies below $14,400,000\$$ are efficient and fluctuations in fuel prices affect all decisions. For busy ports, subsidies can attract more retrofitted ships and reduce emissions. The government could adjust subsidies based on service time and berthing power, and regional preferences should be investigated for optimal policy implementation.

The main takeaway from the study presented by Wang et al. (2022) is that the key factors that influence the effectiveness of the ships/ports interface are related to the number of ships that benefit from the subsidy and install shore side electricity technology on board. Interestingly, increasing the potential number of benefiting ships that could install shore side electricity technology will reduce the amount per ship due to its lower diffusion. They report a utilization rate above 85% even with subsidies of $5,000\$$. Finally, Wang et al. (2023) present a follow-up investigation to model the role of subsidies in identifying how to combine and fund the adoption of two types of emissions reduction solutions, scrubber and shore power supply. In this paper, the authors address the need to find the optimal subsidy level (especially since governments have limited resources to distribute) against shipping companies that try to find the least expensive option to comply with regulations. This follow-up study finds that increasing the number of large ships equipped with scrubbers and shore power devices reduces the total subsidy required due to economies of scale. As the size of the ship increases, the cost gap between energy supply methods narrows, leading to lower subsidies. Increasing the number of equipped ships further reduces subsidies, and each subsidy corresponds to a specific utilization range, allowing the government to adjust subsidies based on desired utilization levels. These findings can guide the implementation of subsidies to encourage the adoption of green technologies in shipping.

2.3. Previous ABM works on green technology adoption and targeting incentives

ABM is a well-known simulation technique for modeling complex systems through a population of autonomous entities known as agents (Bonabeau, 2002; Epstein, 1999). This modeling technique is mainly made up of agents that make autonomous decisions based on their own behavioral rules, interacting with others in a social network and the environment. ABM also considers a bottom-up approach in which microrules of behavior are observed and analyzed at the individual level and emerging outcomes at the macro level (Rand and Rust, 2011). ABM is a valuable simulation tool to analyze what-if scenarios, facilitating the evaluation of strategies before their implementation in the real world, thus reducing the risk of applying them without testing.

The ABM methodology has become a popular method for analyzing the adoption of green technologies or the promotion of policies for green technologies (Ribeiro-Rodrigues and Bortoleto, 2024). Among the most studied green technologies in the ABM literature are the adoption of electric vehicles (Shafiei et al., 2012; McCoy and Lyons, 2014; Huang et al., 2021) and alternative fuels in the automotive industry (Zhang et al., 2011; Stummer et al., 2015). Rai and Henry (2016) presented an overview focused on consumer energy choices with a particular emphasis on how to create and provide the adoption of green technologies using ABM. Hesselink and Chappin (2019) provided a systematic review of the adoption of energy efficiency using ABM, highlighting how such models can help formulate concrete policy recommendations, such as tax reductions. Shi et al. (2020) explored the relationship between information quality for potential users and technological acceptance among small and medium companies, and how inter-firm networks interrelate with information flow and the quality of technological diffusion.

Specifically in the maritime industry, ABM has been used to analyze policies that promote the diffusion of cleaner shipping technologies. Karslen et al. (2019) analyzed split incentives of agents with imperfect information and their relationship with climate-energy policies in the diffusion of one type of WPT. Chica et al. (2023) used ABM to study the effects of different policy and market scenarios (namely subsidies, fuel prices, and networking) on the adoption of WPT retrofitting solutions, including three WPT options. More recently, (Mahmoudi et al., 2024) proposed MATISSE-SHIP, an ABM that shows the potential impacts of retrofitting on the shipping industry and the barriers and incentives that may affect the adoption of low-emission technologies.

The ABM literature has also explored the drivers of the adoption of green technology. Agents decide to adopt based on internal factors such as benefits and capability, as well as external factors related to the relationships and networks between agents (Kiesling et al., 2012; Zhang and Vorobeychik, 2019). Kowalska-Pyzalska et al. (2014) highlighted the role of consumer opinion and its susceptibility to change as key factors. Pakravan and MacCarty (2020) suggested that a better understanding of user intentions is needed and how these intentions translate into behavior. Byrka et al. (2016) focused on the importance of social factors and the difficulty of participation in the adoption of green products and practices.

The social role of adoption is important and, within this framework, the identification of key players and the development of strategies to target them can significantly influence and accelerate the spread of information and the adoption of innovations (Mbaru and Barnes, 2017). This identification and application of incentive policies to a reduced subset of players is known as targeting, mainly of key players (Ramkumar et al., 2022). Although there are numerous examples of ABM focused on targeting key agents for the diffusion of innovation (Delre et al., 2007; Van Eck et al., 2011; Chen et al., 2021), there is less research on targeting agents with a focus on incentive policies and specifically for green energy and green technology. The closest example is the model of Ramkumar et al. (2022). The authors used ABM to test various network-based targeting strategies in inter-firm networks. The targeted companies are informed about green technology, after which they decide whether they want to adopt green technology.

3. Model design

This section provides a detailed description of the proposed model for WPT adoption and the application of targeting policies. First, Section 3.1 introduces the general scheme of the model. Section 3.2 explains how to incorporate targeting policies into the model. Then, Sections 3.3, 3.4, and 3.5 describe the main three modules of the model. Section 4.2 details the real data used when feeding the model and the experimental setup.

3.1. General model structure

The agent-based model represents a population of N vessels and simulates the adoption of WPT over a period of time T. Each time step $t \in \{0, ..., T-1\}$ of the simulation represents a month to allow flexibility when having events and decisions for the shipowners without burdening the computational time. At the beginning of the simulation, all vessels $i \in \{1, ..., N\}$ have fuel-based technology by default, so initial adopters are not considered given the actual low adoption rate of WPT in the maritime industry. The simulation follows three different phases: a) targeting incentives to seed vessels (i.e., those targeted by incentives); b) acquiring awareness of WPT by the vessels; and c) their final WPT adoption decision. It is important to note that the vessels must be aware of the existence of the technology to be able to adopt it. Once they are aware of the technology, they decide whether to adopt it using an adoption heuristic that combines economic and social driving factors. A flow chart showing the main stages of the model is shown in Figure 1. A detailed description of the model is given in the following subsections.

The WPT to be adopted is characterized by a set of characteristics to be considered by the shipowners of the vessels of the population. This set of characteristics includes the monthly maintenance cost of the technology (C), the installation or capital costs (K), and the reduction ratio in fuel consumption when the WPT is installed ($\sigma \in [0, 1]$). These features are fixed for the whole simulation period and all vessels in the population when making their decision to adopt or not. In contrast, the population of vessels belongs to different shipowners and has heterogeneous characteristics. The main characteristics of each vessel $i \in N$ are the following three:

- $y_i^0 \in \{1, ..., Y\}$: represents the age of the vessel in years at the beginning of the simulation $t = 0$. The age of the vessels is used to calculate the remaining months of use of the retrofit population (r_i) with a global maximum lifetime of 30 years ($Y = 30$).
- EC_i represents the expected consumption of energy (namely fuel) of the vessel i under averaged climatic conditions and maritime operations.
- $a_i^t \in \{0, 1\}$ indicates whether the vessel i is aware of the technology ($a_i = 1$) or not ($a_i = 0$). This variable is dynamic and can change at each time step t. We will provide more details in Section 3.3.

Furthermore, the population of N vessels is connected through an artificial social net-

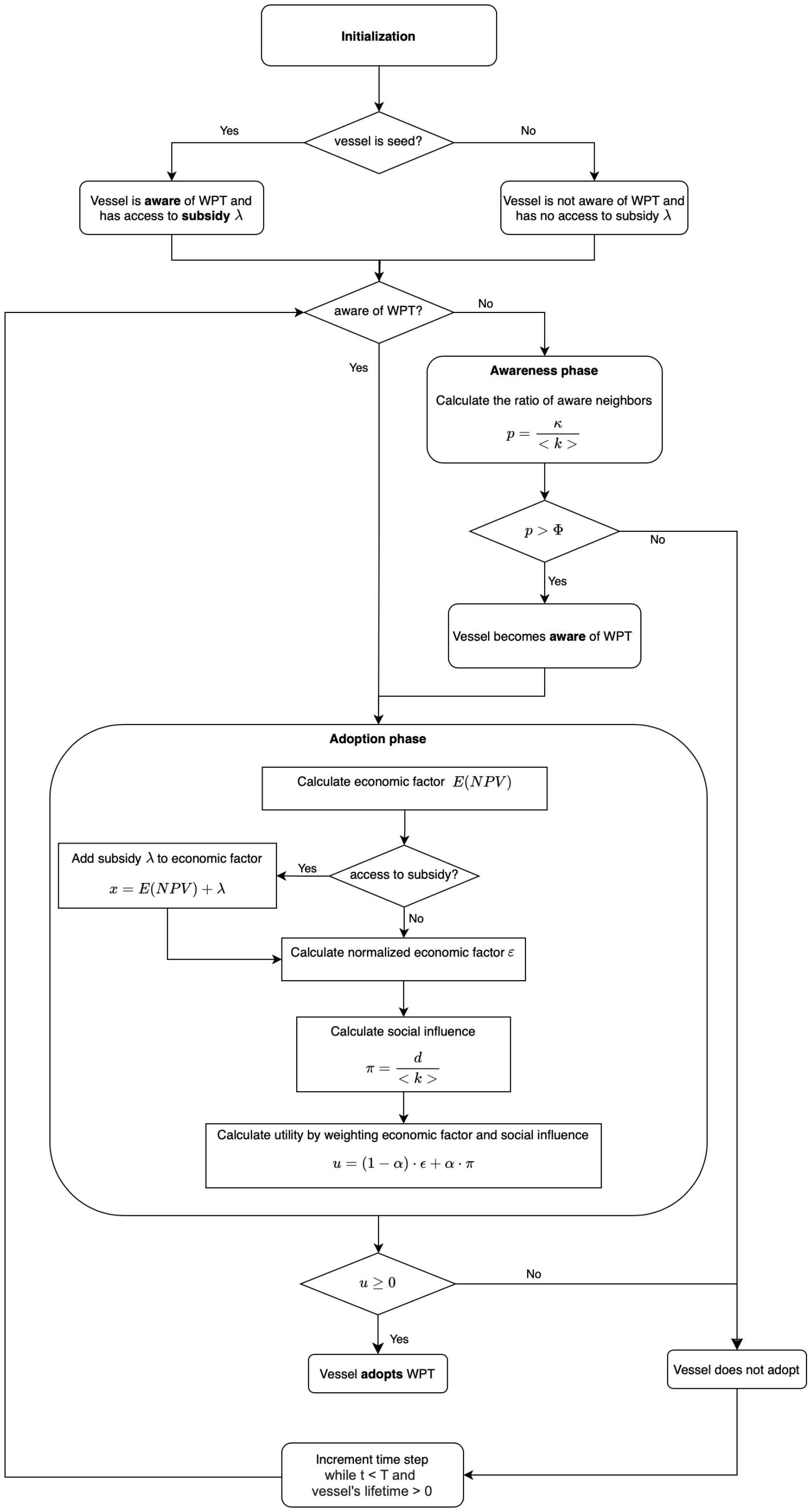


Figure 1: Flowchart of the WPT adoption for a single vessel, applicable to all vessels in the population.

work (Barabási and Albert, 1999; Watts and Strogatz, 1998), which represents the relationships between the vessels. In particular, we choose a scale-free network (Barabási and Albert, 1999) given its proximity to real social networks. These networks follow a power-law degree distribution. This means that most nodes have few connections, while some nodes, known as hubs, have many connections.

3.2. Selection of vessels for targeting policies

To address the objective of selecting micro-incentive policies, we need to target just a subset of $s \in \{0, 1, ..., N-1\}$ vessels of the population. As we will see in the remaining sub-sections, the main idea for these targeted vessels (or seeds for adoption) is to be aware of the WPT and have access to subsidies to alleviate their installation costs.

The selection of vessels is based on the following attributes: age (y_i), energy consumption (EC) and number of direct contacts or neighbors in the social network $\langle k \rangle$, also known as node degree, a common criterion used in the targeting literature (Van Eck et al., 2011; Nöldeke et al., 2020). The latter criteria are combined to assess the convenience of each vessel i to be considered as a seed. Equation 1 shows the weighted combination of these attributes to obtain the quality value of each vessel to be a seed to target (τ_i):

$$\tau_i = \omega_y \left(1 - \frac{y_i}{y_{max}}\right) + \omega_{EC} \frac{EC_i}{EC_{max}} + \omega_{\langle k \rangle} \frac{\langle k \rangle_i}{\langle k \rangle_{max}}, \tag{1}$$

where ω_y, ω_{EC}, and $\omega_{\langle k \rangle}$ are weights within $[0, 1]$ that are properly combined to calculate τ satisfying $\omega_y + \omega_{EC} + \omega_{\langle k \rangle} = 1$.

At the beginning of the simulation, a number of s seed vessels are chosen to apply the specific subsidy policies. The algorithm for identifying seed vessels works as follows. First, we calculate, for each vessel i, its value τ_i. Second, the algorithm sorts the vessels according to their τ_i values in descending order. Finally, the highest s vessels are picked as targets. Similar approaches have been followed in the literature, such as in Chica and Santos (2023). As an example and according to Equation 1, newer vessels with higher node degrees and higher estimated EC will have higher τ values and greater chances of being considered for targeting. In addition, the calculation τ for selecting the seeds s will depend on the weights. In the experimental section, we will investigate the most suitable weight values.

3.3. Awareness phase

This awareness mechanism enables shipowners to have knowledge about WPT, required to assess whether the technology is appropriate for their vessels. In addition to knowing the existence of the technology, this phase aims to know its main characteristics, including fuel savings, costs and the possibility of installing the technology in the vessel. We employ a well-known innovation diffusion process called the complex threshold contagion model (Centola and Macy, 2007), similar to other ABM works on the adoption of green technologies (Ramkumar et al., 2022).

Thus, at each time step t, a vessel i that is unaware of the WPT will become aware (that is, $a_i = 1$) if the fraction of neighbors who are aware (p_i^t) exceeds a global awareness threshold $\phi \in [0, 1]$. Equation 2 defines this process, where $\langle k \rangle_i$ is the number of neighbors of i on the social network and κ_i^t is the number of neighbors of i who are aware of the technology at time step t.

$$p_i^t = \frac{\kappa_i^t}{\langle k \rangle_i}. \tag{2}$$

3.4. Economic driving factor calculation

A key aspect when adopting a new technology as WPT is the economic impact, usually calculated by the expected net present value $E(NPV)$, defined in Equation 3, as in previous related works (Karslen et al., 2019; Chica et al., 2023):

$$E(NPV)_i^t = \sum_{1}^{r_i} \frac{F_i^t - C}{(1 + DR)^t} - K, \tag{3}$$

where DR is a discount rate (set to 0.085 as in Lopolito et al. (2013); Karslen et al. (2019)). F_i is the monthly fuel savings of vessel i when having the WPT under averaged conditions by computing the fuel savings factor of the technology σ, the monthly dynamic fuel prices $f(t)$, and the fuel consumption of the vessel EC_i for a given sailing distance. Specifically, fuel savings for vessel i using WPT, noted as F_i, is given by $F_i^t = \sigma \cdot EC_i \cdot f(t)$. The higher F_i is, the more financially beneficial is WPT for vessel i.

In our proposed method, we incorporate incentives policies in the calculation ($E(NPV)$), with the aim of encouraging the adoption of technology by providing subsidies to a specific subset of vessels rather than providing subsidies to the entire population, as previously done in the related literature. A vessel agent i, if selected as one of the subset of s agents to be targeted for incentive policies, is favored with a subsidy monetary value λ by reducing installation costs K. Therefore, we can extend the economic factor for the agent i to adopt WPT, x_i, as in Equation 4.

$$x_i^t = \begin{cases} E(NPV)_i^t + \lambda, & \text{if vessel } i \text{ is targeted} \\ E(NPV)_i^t, & \text{otherwise.} \end{cases} \tag{4}$$

The economic driving factor must be normalized within the range $[-1, 0]$. The normalization of x_i within this range is computed as follows. First, a theoretical minimum x_{min} is defined, assuming the worst adoption scenario based on the assumption of having free fuel ($f(t) = 0, \forall t$) and the maximum number of operational months for the vessel (that is, $r_{max} = 360$). Therefore, the normalization of the economic factor is performed according to Equation 5, with x_{min} equal to $\sum_1^{r_{max}} \frac{-C}{(1+DR)^t} - K$.

$$\epsilon_i^t = \begin{cases} 0, & \text{if } x_i^t \geq 0 \\ \frac{x_i^t - x_{min}}{0 - x_{min}} - 1, & \text{if } x_{min} < x_i^t < 0. \end{cases} \tag{5}$$

In this formulation, ϵ_i^t represents the normalized value of x_i^t. If x_i^t is nonnegative, ϵ_i^t is set to 0. If x_i^t falls between x_{min} and 0, it is scaled and shifted to fit within the range $[-1, 0]$, using x_{min} as reference.

3.5. Adoption phase based on economic and social drivers

When a vessel i is aware of WPT ($a_i = 1$) and is operational, each vessel can decide whether or not to adopt WPT based on a utility heuristic function. We consider a vessel to be operational while its remaining months of operation are greater than zero (i.e., $r_i > 0$). This variable r_i is updated annually, starting at $t = 0$ from the initial age of the vessel (y_i^0).

Our adoption heuristic follows the existing literature on the adoption of innovations (Delre et al., 2010). Here, the adoption decision of an agent is determined by a weighted average of internal factors and external social influence of neighbors. We set internal factors as the economic component of the decision (that is, fully rational). The utility function of Equation 6 weights this average of internal/economic factors $\epsilon_i^t \in [-1, 0]$, already defined in Section 3.4, and a social influence π_i^t. This social influence corresponds to the impact of adoption by others and can be related to showing the installed technology through conversations among shipowners, social media interactions, or networking activities. The parameter $\alpha \in [0, 1]$ determines the weight given to social influence in the adoption decision.

$$u_i^t = (1 - \alpha) \cdot \epsilon_i^t + \alpha \cdot \pi_i^t. \tag{6}$$

The social influence for each vessel i at each step t is calculated as the fraction of neighbors that have already adopted the WPT, defined by Equation 7:

$$\pi_i^t = \frac{d_i^t}{\langle k \rangle_i}, \tag{7}$$

where d_i^t is the number of neighbors that have already adopted the technology at time t and $\langle k \rangle_i$ its degree in the network. It is important to note that this social influence $\pi_i \in [0, 1]$ is different from p, defined in Section 3.3, linked to the knowledge and awareness of WPT. Therefore, an agent i can be aware of WPT without having adopted the technology, affecting neighbors differently.

An operating vessel i that has fuel-based technology at the time step t will adopt WPT if its utility value $u_i^t \in [-1, 1]$ is greater than or equal to zero. This design ensures that the social component only has a positive impact on the decision-making process while allowing for the potential negative impact of the economic driving factor, which is different and richer than previous similar approaches in the literature where both components affect in exactly the same way. The utility will be equal to or greater than 0 when the normalized economic factor is 0. In other words, the non-normalized economic component is not negative, indicating that the adoption of the technology does not involve losses. This property guarantees adoption regardless of the value of the social component. However, if the normalized economic component is negative (i.e., the non-normalized economic component is negative), adoption can occur when the positive social value is sufficiently high to compensate for a relatively low economic factor.

4. Experimental setup

4.1. Vessels, WPT pilot vessel and fuel scenarios data

Information and data on WPT were obtained through the EU-funded Interreg WASP project (*https://northsearegion.eu/wasp*). The project collected data for the VentiFoil WPT, which was installed on the pilot vessel of the case study used for the experiments. VentiFoil is a particular type of rigid sail that works with mechanical aeration, generating a suction effect, analogous to that of airplanes. This is an emerging technology which was tested by Econowind, its supplier, as part of the WASP project (ECONOWIND, 2024). The only previous research related to this technology, also in connection with the WASP project, evaluated the energy savings of WPT (Ghorbani et al., 2024). This previous study combined field estimations with computer modeling to estimate fuel savings of the VentiFoil for one particular type of vessel under different sailing conditions.

The VentiFoil technology was installed on a pilot vessel, allowing us to obtain the values shown in Table 1. Therefore, for our experiments, the parameters C, K, and σ were set to those of Table 1 to be considered by the shipowners of the population when making their adoption decision.

WPT VentiFoil feature	**Value**
Installation costs (K)	321,151€
Monthly maintenance costs (C)	535.25€
Fuel savings (σ)	2.875 %

Table 1: Data about the WPT VentiFoil from the pilot vessel of the WASP project.

With respect to the population of vessels, we used the same data as in Chica et al. (2023). They consist of real data containing information on $N = 6,009$ vessels extracted from the Clarksons database and focused on all types of vessels with dead weight tonnage from $2,000$ to $6,500$. This value is derived from the Clarksons study (Clarksons Research, 2024) and internal data from the WASP project pilot ships. This set of $6,009$ vessels is the same as in Chica et al. (2023) to facilitate the comparability of the results and includes a heterogeneous population of vessel types (tankers, bulk carriers and general cargo ships).

Different sailing distances were considered: $26,000$, $43,000$, $50,000$ and $60,000$ nautical miles. These distances directly affect the EC of the vessels in the population. Each vessel in the population will have a different EC_i, based on the scenario considered of the yearly sailing distance. The method for estimating the EC of the vessels has been previously described in Chica et al. (2023) (Supplementary Material), which makes use of their specific features. In the data set, the EC of each vessel was estimated following IMO Resolution MEPC.245 (66) (Marine Environment Protection Committee (MEPC), 2014), and the information required for each ship included the power of the main and auxiliary engines, the specific fuel consumption and the speed of the ship. Data such as main engine power, auxiliary engine power and fuel consumption were sourced from the Clarkson World Fleet Register, 2022. Some ship-specific correction factors were applied for certain factors, such as ro-ro cargo or passenger ships. Similarly, some ships had missing data, such as volumetric displacement, in which case average values for similar ship types were used. Finally, the speed of each type of ship was determined according to case studies or external sources.

Finally, the fuel price at the beginning of the simulation was set at 500€/mt. However, this initial fuel price increases during the simulation in two pricing scenarios. First, a monthly pessimistic scenario in which the price of the fuel increases linearly by 0.5% each month for 360 months of simulation. Second, a more optimistic scenario based on the year in which the price also increases linearly but by 5% every year. These two scenarios were used in previous works, although other pricing scenarios can be found in the literature (Köhler et al., 2022; Cariou et al., 2023).

4.2. ABM parameter specification

Regarding the ABM simulations, we executed the model for 30 independent Monte Carlo (MC) runs for all experiments, averaging all the results of these MC runs. We ran the simulation in 360 steps, which means 30 years of simulation. Thus, all the results shown in the experiments come from terminated simulations in 360 steps. The maximum lifetime of the vessel Y was established at 30 years, following a previous work (Karslen et al., 2019). We generate four different network instances using the Barabasi–Albert preferential attachment algorithm (Barabási and Albert, 1999), which uses a parameter m to modulate the growth rate of the scale-free network (SF) and its final density. More specifically, we generated SF2, SF4, SF6, and SF8, which correspond to values 2, 4, 6, and 8, for m, respectively. This is a natural way to consider a social network of peers when no real information is available.

We established the values for the awareness threshold ϕ and the social influence weight α following previous literature due to the lack of historical data on WPT in the maritime industry. These two parameters are independent of the size of potential adopters in an industry but related to the social dynamics when adopting a new technology. Although a sensitivity analysis of (ϕ, α) was performed when validating the model, we set ϕ at 0.4 and the weight of social influence α to 0.5 to be consistent with a previous work (Ramkumar et al., 2022) and maintain a balance between social and economic factors. Given the lack of knowledge of WPT, only those s vessels selected by targeting incentive policies are aware of the technology ($a = 1$) at the beginning of the simulation. These target vessels will be those initiating awareness of WPT to the rest of the vessels.

5. Results

First, we run a diverse set of targeting strategies following different criteria to obtain the initial vessels to be incentivized in Section 5.1. Later in Section 5.2 we explore how changing the initial number of seeds and budget for subsidies impact the adoption. Finally, Section 5.3 studies how different scenarios affect WPT adoption for some targeting strategies.

5.1. Impact of different targeting strategies

This section presents the results of a set of different incentive targeting strategies. Specifically, our objective is to compare the effects of different strategies for targeting policies and compare them with the baseline of having a uniform allocation of subsidies to all vessels, as done in (Chica et al., 2023). For all targeting strategies and the baseline, the total budget for subsidies is kept constant for a fair comparison.

We do not just apply one targeting strategy, but a set of them by combining three different criteria (measured by weights $[\omega_y, \omega_{EC}, \omega_{\langle k \rangle}]$) when sorting and selecting the seed vessels to target. Specifically, we consider the following eight strategies with the values for the weights:

a) by *age*, where vessels are just chosen by its age attribute y $[1, 0, 0]$;

b) by the *EC* of the vessel: $[0, 1, 0]$;

c) by their *degree* $[0, 0, 1]$;

d) by a combination of *age-EC* $[0.5, 0.5, 0]$;

e) by a combination of *age-degree* $[0.5, 0, 0.5]$;

f) by a combination of *EC-degree* $[0, 0.5, 0.5]$;

g) by a combination of the three criteria *age-EC-degree* $[0.33, 0.33, 0.33]$;

h) an unbalanced combination of *0.25EC-0.75degree* $[0, 0.25, 0.75]$ to inject more importance to their potential social activity.

The same number of seeds are considered in the experiments. Specifically, we consider 10% of the total vessels ($s = 0.1N$). In addition to the previous strategies, a random strategy (*random*) is employed in which the s seeds are located at random without using the weights mentioned above. The results are obtained for a fixed scenario having an SF4 network, a sailing distance of $43,000$ nautical miles per year, and updated monthly prices. The baseline *all* uses the same budget as all previous strategies, but is distributed uniformly for all vessels N. As described in Section 3.2, the targeted seed vessels s are aware of the WPT at the beginning of the simulation. Therefore, in the case of uniform distribution for all vessels, an initial WPT awareness of 10% is also established for a fair comparison.

Figure 2 illustrates the adoption rate of WPT when the global budget is uniformly distributed throughout the population (noted *all*) with respect to all the proposed targeting policies. Taking into account that the maximum amount of the subsidy per vessel is $321,151$€ (equivalent to covering the full installation costs), we establish the following budget scenarios: $193,011,751$€ (subsidizing 100% of the installation costs for s seeds), $174,710,035$€ (90% subsidizing), $154,408,920$€ (80% subsidizing) and $135,107,805$€ (70% subsidizing). These total budgets are transformed into the following per vessel subsidy amounts within the *all* approach: $32,120$€, $28,908$€, $25,696$€, and $22,484$€, respectively.

From Figure 2 we observe that the *all* approach results in nearly zero adoptions in all budgets due to insufficient incentive levels. However, by using the same global budget but directing the subsidies to the target set of vessels, the WPT adoption rate is clearly increased. In particular, targeting vessels focused on their degree (social activity) results in at least 25% adoption for the highest budget considered. As expected, all targeting policies are more effective as the total budget increases. Interestingly, when considering lower budgets, degree targeting is not the best option, but is outperformed by those targeting policies using EC as a criterion.

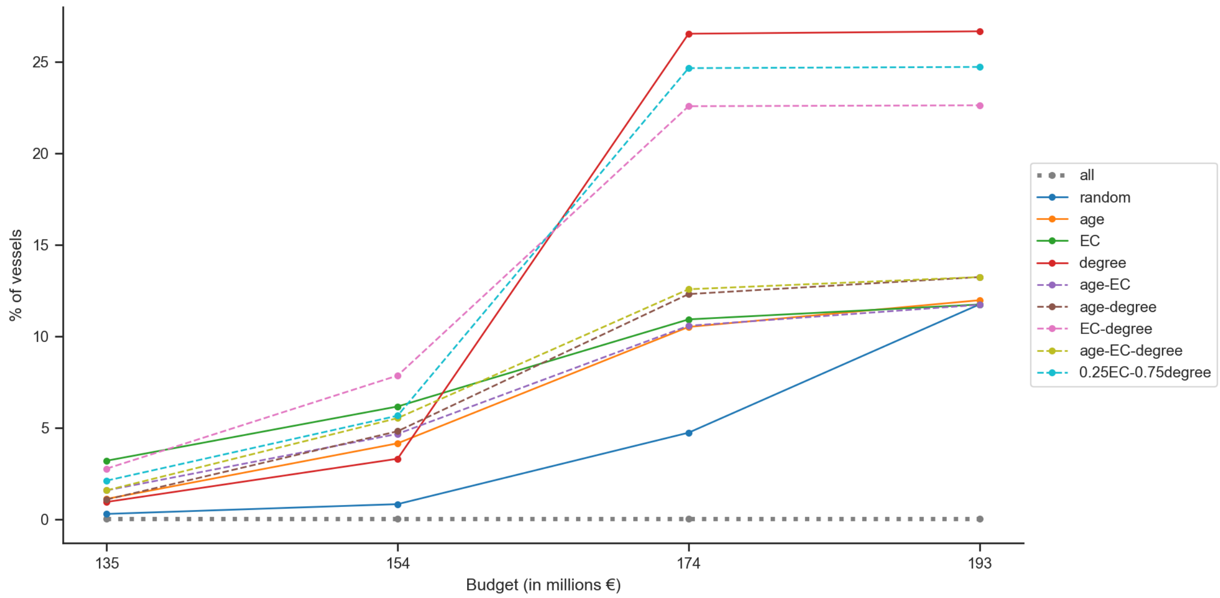


Figure 2: Line plot showing the WPT adoption rates (Y axis) for different total budgets (X axis) when considering alternative targeting strategies and subsidies for all the vessels. The simulation was carried out considering a sailing distance of $43,000$ nautical miles per year, monthly updated fuel prices, SF4 network, $\phi = 0.4$, and $\alpha = 0.5$. We set the initial number of seeds to 10% and, for the *all* strategy, we considered an initial awareness of 10%. The degree-based strategy is the best one for the highest budgets while using EC as a criterion is necessary to boost the adoption rate when having lower total budgets.

5.2. Performance of targeting policies under different numbers of initial seeds and subsidy budgets

In this section, we conduct a deeper comparative analysis of all the proposed targeting strategies and compare them with respect to the random strategy. For this purpose, we perform a sensitivity analysis (SA) on two key parameters: number of initial seeds s and subsidy for installation costs (λ). Specifically, the percentage of selected seeds ranges from 1% to 10% and the installation cost subsidy λ from $200,000$€ to $330,000$€, with incremental steps of $5,000$€. We focus our analysis on the results obtained considering a sailing distance of $43,000$ nautical miles per year, $\phi = 0.4$, and $\alpha = 0.5$, the SF4 network, and updated monthly fuel prices (similar dynamics were observed under the yearly updated fuel price scenario in preliminary experiments).

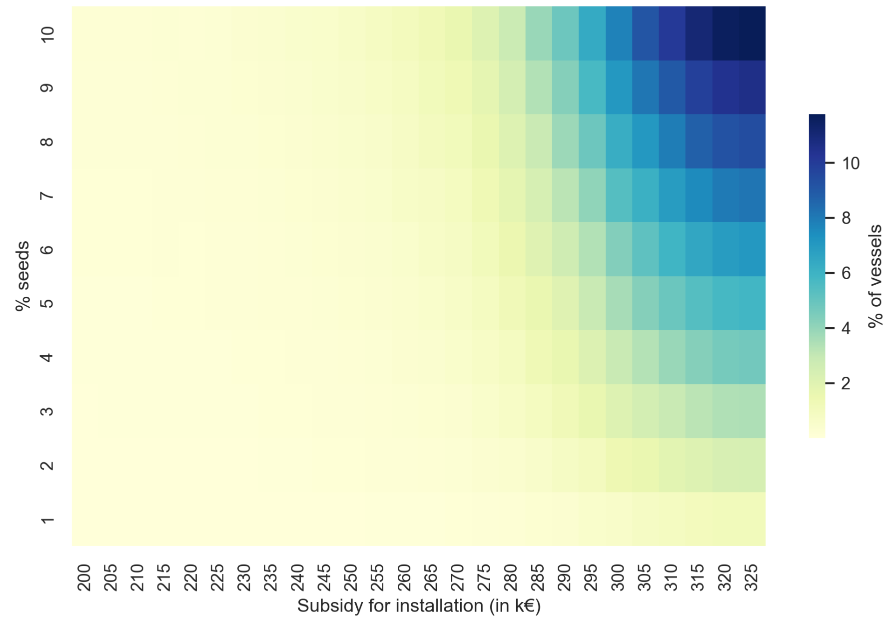


Figure 3: Heatmap showing a sensitivity analysis (SA) on per vessel installation cost subsidy λ and percentage of seeds of the population N when randomly target seeds. Values are the percentage of vessels adopting WPT. Under this random targeting, significant adoption only occurs when employing a subsidy greater than $290,000$€.

We start the results discussion by showing two different panels of heatmaps obtained from the experiments. First,the heatmap in Figure 3 illustrates the percentage of vessels adopting WPT after applying a random targeting strategy, serving as the baseline for comparison. From this heatmap of the random strategy, we see that subsidies below $300,000$€ are not sufficient to start the diffusion of WPT, as even the targeted vessels are not adopting the technology. When subsidies exceed $300,000$€, practically only those vessels that receive subsidies adopt the technology. Therefore, randomly selecting the targeted vessels does not extend the adoption of the technology beyond those targeted vessels.

Second, a panel of heatmaps showing the relative differences in the adoption rates of WPT for all policies with respect to the random strategy (Figure 4). Such relative differences are based on considering random targeting as a reference. The higher the difference with respect to the targeting policy under study, the darker the color in the corresponding heatmap. In this experiment, all policies outperform the random policy in terms of adoption rates, as the cells of the heatmaps are blue, indicating a positive increase in adoption. Furthermore, increasing the percentage of seeds (Y axis of the heatmaps) increases the adoption rates across all policies. However, this variable appears less critical than the subsidy amounts since, when not having an adequate subsidy, adoption rates do not increase significantly, even with a higher percentage of seeds.

The degree policy emerges as the most effective when high budgets are considered, following the results of the previous sub-section. Under these budget conditions, degree-based targeting strategies achieve adoption rate differences of around 20%. EC-based strategies seem to be the most consistent for the whole range of subsidy budgets (X-axis). However, policies using the age of the vessel and EC obtain an increase of approximately 6%, lower than the optimal conditions for degree-based strategies.

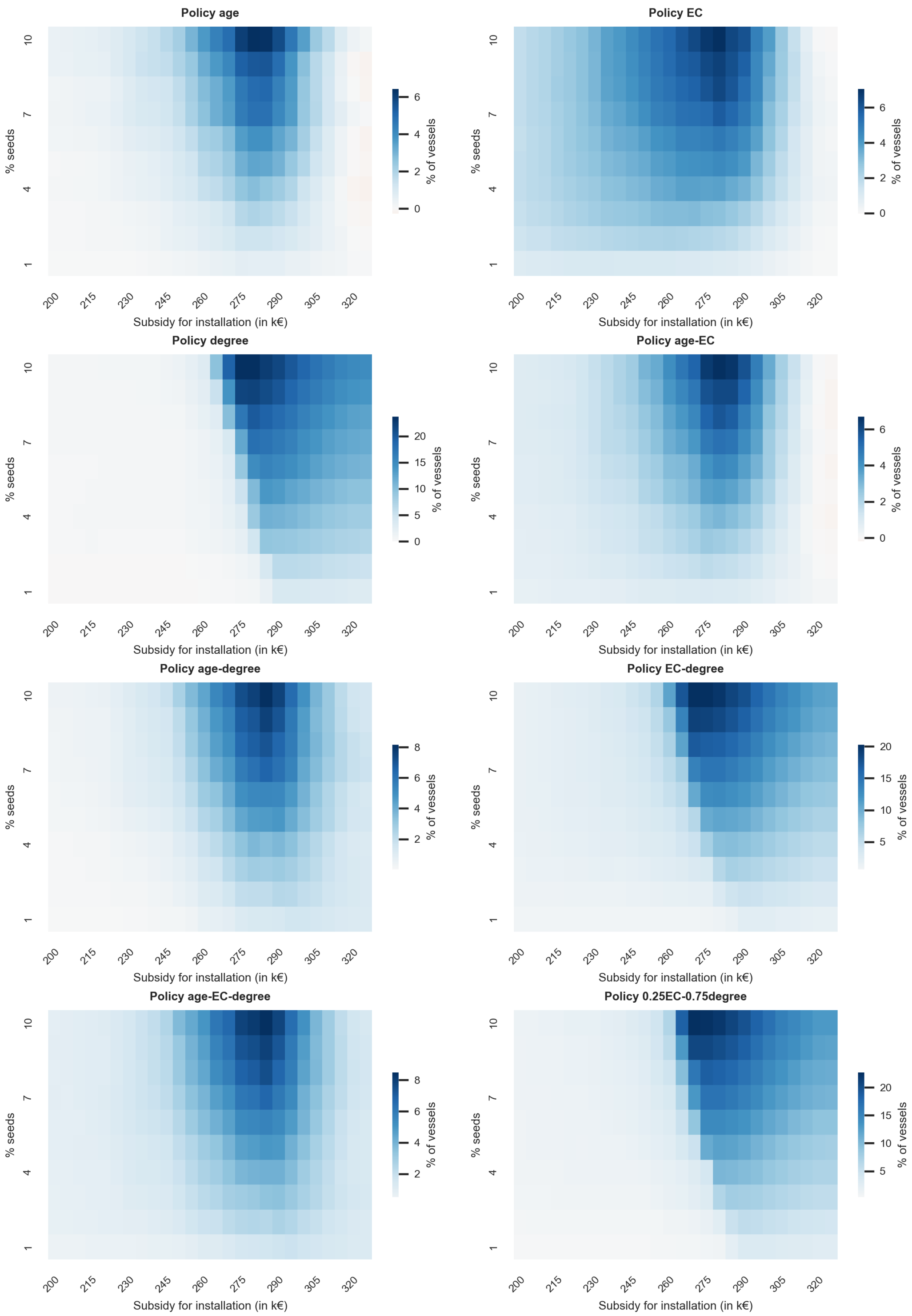
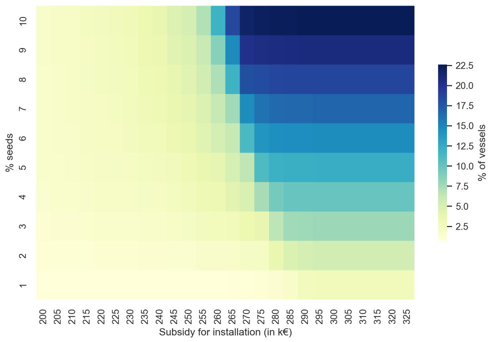
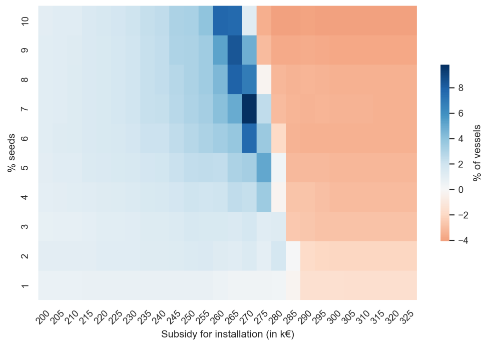


Figure 4: Panel of heatmaps showing, for each targeting policy, the relative difference in the WPT adoption rate with respect to the targeting policy of selecting seeds at random. Each heatmap shows a sensitivity analysis (SA) on installation costs subsidy λ and percentage of seeds N. It can be seen how all the non-random targeting policies obtain better results than those shown in Figure 3 for the random targeting strategy for most of the subsidy values.

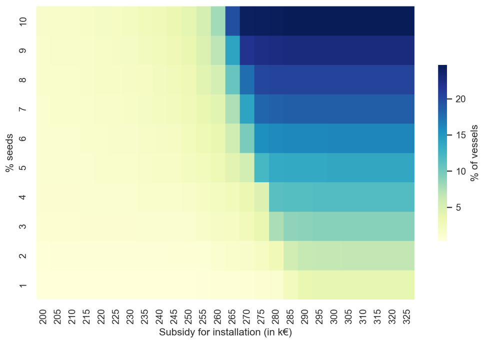
Four heatmaps are shown in Figure 5 to better compare degree- and EC-based targeting policies. Figures 5a and 5c show the adoption rates of the EC-degree and 0.25EC-0.75degree policies, respectively, while Figures 5b and 5d compare those strategies with respect to the full degree strategy. Both policies behave very similarly, with the EC-degree policy achieving slightly higher overall adoption rates. As suggested in the previous section and as shown in Figures 5b and 5d, for certain cases ($\lambda < 250,000$) these combined approaches demonstrate improvement in the adoption of up to 5% over the degree policy. This improvement occurs because, when subsidies are not substantial, selecting vessels based only on the number of contacts does not ensure their adoption (although these vessels are essential for spreading the technology adoption later). In contrast, vessels with higher EC are more likely to adopt the technology, even with lower subsidy amounts. If subsidies cover most of the installation costs, using an EC criterion is not adding value for a significant adoption. Interestingly, there is an area in the heat map, $250,000 < \lambda < 275,000$ approximately, where one can find the maximum positive differences. When the subsidy budget lays on that space, using EC as a criterion is crucial to boost the adoption of WPT.



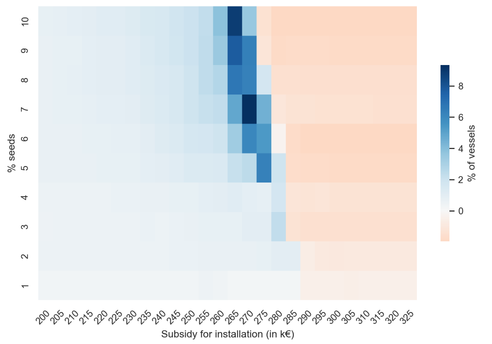
(a) **EC-degree policy**



(b) **EC-degree policy difference over full degree policy**



(c) **0.25EC-0.75degree policy**



(d) **0.25EC-0.75degree policy difference over full degree policy**

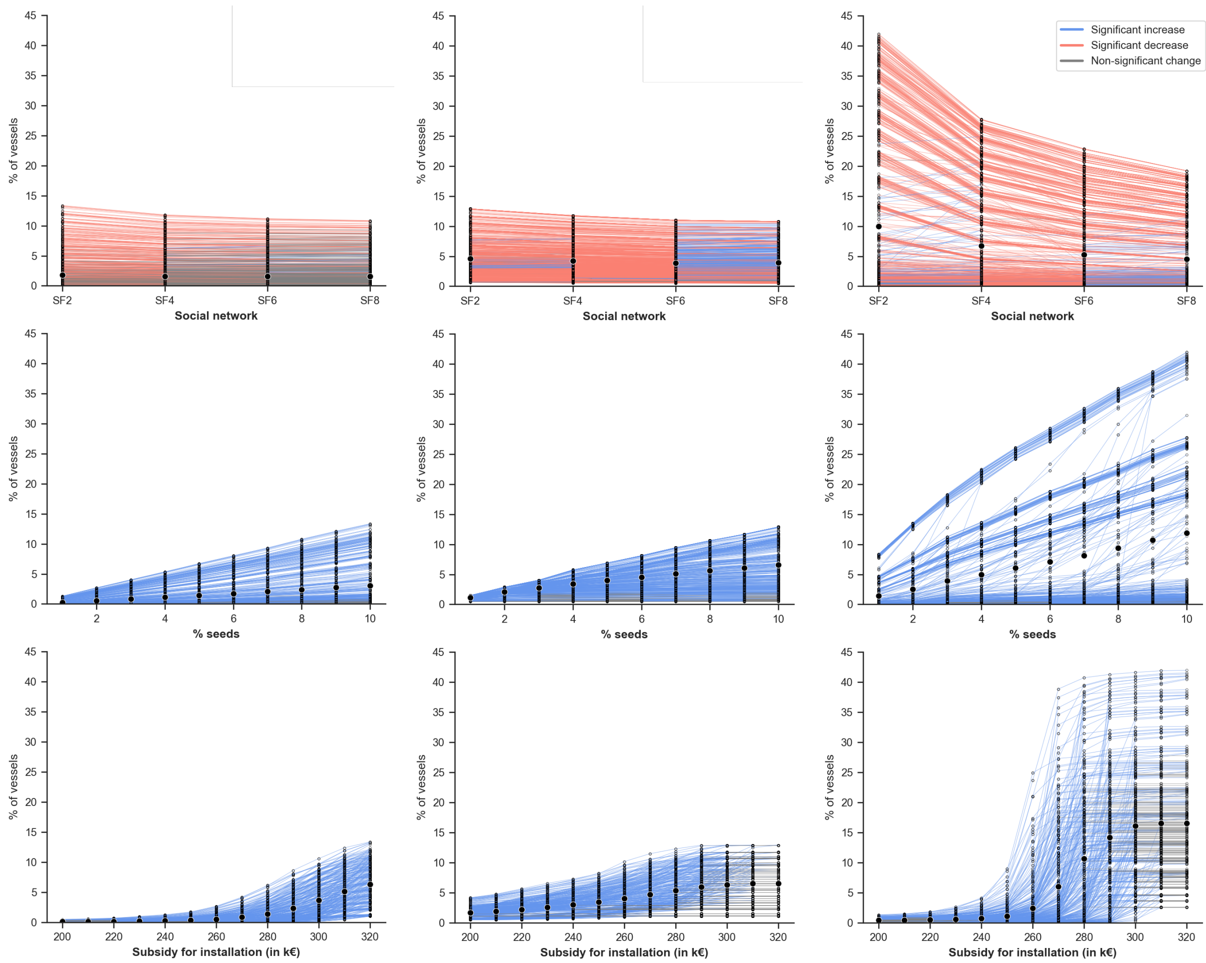
Figure 5: Panel of four heatmaps showing WPT adoption rates (left column) and the relative difference in WPT adoption rates when combining EC and degree with respect to a targeting strategy of just considering the degree (right column). Each heatmap represents a sensitivity analysis (SA) on per vessel installation cost subsidy λ and percentage of seeds of the population N. Results for a proportional combination of EC and degree (plot (b)) are more significant for both positive and negative differences. Three main areas are observed (low increase, high increase, low decrease), depicting when EC is useful for targeting vessel seeds.

5.3. Analysis of the best performing targeting policy on different scenarios

In our final set of experiments, we examine how different scenarios for sailing distance, fuel pricing evolution, social network topologies, subsidies, and number of initial seeds affect the results of the targeting policies in terms of final WPT adoption. We set for the whole experiment three targeting strategies: the full degree-based targeting strategy, the EC-based targeting strategy, and the random targeting strategy. With respect to the scenarios to be considered, we run the simulations for sailing distances of $26,000$, $43,000$, $50,000$ and $60,000$ nautical miles, both the monthly and yearly fuel pricing scenarios (described in Section 4.2), and SF topologies with different densities (from SF2 to SF8). Finally, as in previous subsections, different budget subsidy allocations and number of initial seeds are also considered.

The objective of this experiment is to extract insights that enrich our understanding of the relationship between scenarios, policies, and the output of the simulation model. To do that, we run the model for all possible combinations of scenarios. Specifically, our analysis considers $4,160$ different scenario settings, including the different settings in pricing scenarios, social network densities, sailing distances, percentage of seeds and installation cost subsidies. We visualize the impact on the WPT adoption rate for all scenarios using the S-ICE curves (Borgonovo et al., 2022). S-ICE curves are a modification of the ICE curves adapted to the stochastic nature of ABM. In addition, we show the partial dependency plots (PDP) (Friedman, 2001) which correspond to the mean of the ICE curves, and show the average effect that a variable has on the model output. The panels 6a, 6b, and 6c show these S-ICE curves with their PDP attached to them. Each dot represents the adoption rate under each scenario (specific parameter configuration), averaged for the 30 MC runs, while the line connecting two dots illustrates the change between scenarios when a single parameter varies.

We specifically show the results for variations in the densities of social networks, the percentage of seeds, and the installation cost subsidies on the X-axis, while the vertical axis represents the percentage of vessels adopting the WPT. We do not show variations in pricing scenarios and sailing distances as they are considered trivial. The large black dots on each vertical line represent the corresponding PDP, that is, the average adoption rate across all scenarios. The statistical significance of changes in the plots of Figures 6a, 6b and 6c is determined using a two-sample t-test at a 5% level of significance. The red lines indicate a negative change, the blue lines a positive change, and the gray lines a change that is not statistically significant. For example, if the variation from one subsidy amount to the next leads to a higher adoption rate, this change is shown as a blue line. If the variation between subsidy amounts results in a lower adoption rate, it is shown as a red line. If the change in adoption rate is not significant, which means that it does not significantly impact adoption, it is shown as a gray line. We extract the following observations from the S-ICE



(a) **Policy random**

(b) **Policy EC**

(c) **Policy degree**

Figure 6: S-ICE plots for WPT adoption under random (left column), EC (central column), and degree (right column) targeting policies. Each row of the panel shows variations in the densities of the social network, the percentage of seeds to be simulated, and the subsidies for installation in € along the X axis. Each point on the plot represents a unique scenario, while the line connecting two points illustrates the change between scenarios when a single parameter varies. Line color indicates the nature of changes: blue for significantly positive, red for significantly negative, and gray for nonsignificant changes. Partial dependency plots (PDPs) are represented by large dots. Simulations were carried out considering $\phi = 0.4$, and $\alpha = 0.5$.

plots, divided by each variable:

- Social network densities: Analysis of the densities of social networks reveals different behaviors for the three policies. Under the random policy, red lines predominate between SF2 and SF4, indicating a significant decrease in adoption rates. From the SF4 to SF8 scenarios, differences are not significant in many scenarios. The mean adoption rate is low, below 2% with little variation between different densities. On the other hand, under the degree policy, the mean adoption rate is higher, reaching 10% in SF2, and decreases as network density increases. Although most scenarios follow this decreasing trend, the presence of some blue lines indicates nonmonotonic behavior and interactions with other variables. Unlike the random policy, the differences here are significant in all scenarios, with no gray lines. This is expected as the degree policy is based on a network measure, which makes network density a key influencing factor. In short, lower densities correspond to higher adoption rates since degree-based policies are more critical than in a high-density network where vessels have more connections and neighbors in general. The EC-based policy also shows significant differences, but the decrease in adoption rates is less steep compared to the degree policy. In addition, there are quite a few blue lines between SF6 and SF8, indicating nonmonotonic behavior. The influence of social network density on EC policy can be attributed to the fact that, under the EC-based policy, those receiving incentives are likely to adopt due to economic advantages, while the spread of adoption to their contacts depends largely on their connectivity.

- Percentage of seeds: Under the random and EC policies, the mean adoption rate increases as the percentage of seeds increases, following a regular growth trend across all scenarios. The EC and degree policies reach a higher mean adoption rate. The degree policy also shows a significant increase trend in all scenarios. However, the growth is less linear. We can also observe slope changes at some points, with the slope becoming much pronounced above a certain percentage of seeds in some scenarios. Locating these points can be useful to find the optimal seed percentage for each scenario.

- Subsidy for installation: Under the random policy, the mean adoption rate increases from 0% to around 6%, and the differences are significantly positive in almost all scenarios. We observe a steeper slope starting at $260,000$. The behavior of the degree policy differs in several aspects. It starts from a similar mean rate around zero but grows much faster, reaching almost 20%. In this case, we observe a steeper slope between $260,000$ and $290,000$, where the biggest increases occur. Furthermore, from

290,000 in some scenarios and from 300,000 in others, the adoption rate reaches a saturation point. After that point, the differences become insignificant. The subsidies budget shows a strong positive impact on the adoption rate, in which all scenarios start from a value close to zero and evolve to values of up to 40% in the degree policy. The EC-based policy, unlike the previous ones, starts with a higher mean adoption rate (almost 2%) but shows less pronounced growth. We also observe that it reaches saturation points in almost all scenarios, in some cases starting from subsidy levels lower than 260,000. This behavior can be attributed to its initial advantage at lower subsidy levels, as it achieves adoption by a significant portion of the seeds early on. However, further increases in subsidies result in little variation. On the other hand, for the other policies, higher subsidy levels are necessary to achieve significant increases in adoption rates.

In summary, random and EC policies show more regular growth and are less influenced by changes in variables. In contrast, the degree policy is highly influenced by changes and presents nonmonotonic behavior with clusters and pronounced slopes. The degree policy also achieves higher mean adoption rates across all variables, and its maximum values are far higher. Furthermore, we identified tipping points in EC and degree policies, such as in the case of subsidies, providing valuable information for the design of more effective policies and resource optimization. Notably, the subsidy amount stands out as the most influential variable, as can be seen in the pronounced growth of its PDP and in most scenarios.

6. Discussion

From a practical point of view, the main insights that we observe are the following. First, without interventions, the adoption of WPT is practically non-existent, in line with the findings in Chica et al. (2023). Second, with the same global budget, it is more effective to allocate a higher amount of installation cost subsidies to a set of vessels rather than distributing a lower amount across the entire population. Moreover, it is essential to strategically select which vessels to target with the subsidies. The highest adoption rate is reached when the target policy consists of selecting the vessels with the highest number of contacts, as these vessels will positively influence their neighbors to adopt the technology. This fact highlights the important role of social influence, as influential vessels can accelerate the spread and adoption of innovations. This social influence can be seen as the activity of shipowners when attending conferences or workshops, in their networking projects or in their social media.

It is worth noting that, for a mid-level of subsidies, it is more beneficial to consider not only the number of contacts but also the EC of the vessel. This combined policy improves effectiveness, particularly when subsidies are not yet substantial. By selecting vessels with high EC, we ensure that the chosen vessels are more likely to adopt the technology. We also observed that each policy exhibits different behavior across different scenarios, being more or less influenced by certain variables or being more or less regular. In general, it seems that the most influential variable is the installation cost subsidy. Additionally, we observed the presence of saturation points which allow us to identify levels of subsidies from which the adoption rate growth becomes non-significant. Identifying these points ensures that subsidies are neither too low to be ineffective nor too high to waste resources. In summary, these insights highlight the importance of strategic subsidy allocation and the significant role of social influence and subsidy amount in promoting the adoption of WPT.

Subsidies as a policy to improve the adoption of green maritime technology are critical, as evidenced by our findings and supported by the existing literature. Research by Cheaitou and Cariou (2019) highlights that inelastic demand for transport can influence the effectiveness of subsidies compared to fuel taxes, which have varying impacts depending on demand elasticity and fuel prices. Similarly, Chen et al. (2023) indicate that market-based mechanisms, such as carbon levies and emissions trading systems (ETS), have different short-term and cost implications for emission reductions, with ETS often providing more immediate cost-effectiveness. Although much of the literature has focused on these market-based mechanisms, the role of direct subsidies has been less explored. Zhang et al. (2024) demonstrate that state subsidies are crucial for the initial adoption of hydrogen propulsion technologies, as upfront costs and infrastructure requirements cannot be met without government support.

The latter observations are aligned with our findings: targeted subsidies, particularly those directed at vessels with high connectivity and energy consumption, significantly enhance the adoption of WPT. Huang et al. (2023) further support this by showing that subsidies can stabilize and enhance the profitability and greenness of maritime operations, although excessive subsidies need careful management to avoid market chaos. Wang et al. (2022, 2023) provide insights into optimizing subsidy efficiency, showing that targeted subsidies for port operations and specific ship retrofits can maximize environmental benefits. Our research corroborates these findings, demonstrating that strategic allocation of subsidies based on network metrics and vessel characteristics can lead to higher adoption rates and more effective use of resources. This approach ensures that subsidies are neither too low to be ineffective nor too high to waste resources, thus optimizing the green transition in the maritime industry. Therefore, the integration of subsidies with market-based measures and a focus on targeted incentivization could be critical to promoting green technology and achieving substantial emissions reductions in shipping.

Theoretically, our study contributes to the literature on strategies in the field of sustainability transitions. Although contextualized to this sector, there are a couple of lessons that extend beyond shipping and bring insight to organizations in general. Although the literature on socio-technical transitions has extensively analyzed the role of strategic niche management through target policies aimed at supporting the diffusion of given technologies (Schot and Geels, 2008), less iss known about how to target concrete organizations that seek to be promoted and nurtured by public policies. Based on a case study of WPT, we engage in this debate that interlinks sustainable sociotechnical transitions and the role of public policies (Karslen et al., 2019; Chica et al., 2023; Mahmoudi et al., 2024). We acknowledge that this sector is at a critical transition stage and multiple technologies are competing in parallel for dominance in given segments (Urban et al., 2024). Our findings open a key debate in which a more fine-grained analysis of public policies should be undertaken when trying to understand the micro-dynamics of the green transition at work. In this way, we respond to the calls of the socio-technological transition community to expand the methodological toolbox to include complex system simulation techniques (Köhler, 2019).

From a methodological point of view, we can highlight the following facts. Our approach differs when comparing our work with other studies on targeting in green technologies in the ABM literature, where research remains scarce. While other studies use targeting to inform about the new technology (Ramkumar et al., 2022) or for initial adoption (Barbuto et al., 2019), our work uses targeting to provide incentives that facilitate technology adoption. To our knowledge, this approach has not been explored in the ABM green technology literature. Furthermore, while Ramkumar et al. (2022) conducted experiments with firms and Barbuto et al. (2019) with farmers, our study uses real data from vessels in the maritime industry. With respect to the maritime industry, and specifically in relation to Chica et al. (2023), we incorporate a model with greater emphasis on social influence and provide incentives to only a subset of the population rather than the entire population. In addition, our work proposes the design of targeting policies that take into account both the social characteristics of the network and the specific characteristics of the vessels.

7. Conclusions

In this study, we developed an ABM enriched with real shipowners' data and WPT pilot prototypes to simulate technology adoption. Before the awareness and adoption phase of the model, micro-targeting incentives were applied. These micro-policies are the key ingredient of our proposal, as we provide subsidies to a subset of agents based on different criteria rather than distributing them uniformly throughout the population, as done in related studies for green technologies in the maritime industry. Thus, our study significantly contributes to the

ABM literature on green technologies using targeting to provide incentives for technology adoption, unlike other studies that focus on informing about new technologies or adoption based mainly on economic factors.

The main results of the simulation-based experiments are as follows. First, we see that directing subsidies to a strategically chosen subset of vessels achieves higher adoption rates than spreading smaller subsidies throughout the population. Depending on the total budget, the criteria for choosing target vessels change, with degree and EC being the most valuable criteria for seed selection. Specifically, policies based on the degree of vessels in the social network are effective, highlighting that social influence and networking play crucial roles in the adoption of green technologies. All targeting strategies are superior to the adoption rates obtained by subsidizing all the vessels or considering a random selection of the seeds. Under different budget conditions, the use of non-social criteria such as the EC of the vessel is also recommended. This highlights the importance of carefully selecting which vessels are targeted for incentives and not using a general approach. We compared random policies, EC-based and degree-based policies under more than $4,000$ scenarios, and our analysis reveals expected output dynamics in different scenarios while each strategy exhibits different behavior. This variability underscores the complexity of the system and the need for an adequate strategic policy design.

This study presents some limitations. The first limitation is related to the scope of adopting one single type of clean technology. Currently, the maritime sector is undertaking essential investments in research and innovation, and several technologies seek are competing for legitimacy to become the new "low carbon" or "zero carbon" preferred solution in the sector. By recognizing the complexities of modeling different types of technology in one single study, we see the limitation that comes with focusing on one particular kind of technology. However, the goal of the study is not to promote this specific technology over other competing technologies through subsidies, but rather to study the possibilities of targeted subsidies that can help promote green technologies in general. Furthermore, as it is beyond the scope of our study, we do not discuss here how governments should implement incentive mechanisms when introducing targeted subsidies to avoid corrupt practices or inefficient processes. An additional limitation of the model is that the knowledge of WPT is low and the current adoption rate is insignificant according to the Clarksons database. Then, if a targeting mechanism is not applied, there are no other external ways for shipowners to adopt. This design is justified since the focus of the model is to evaluate targeting incentives. However, a redesign of the model would be needed if more general scenarios needed to be applied.

The final limitation is that no information about networking activities was collected. For this reason, an artificial scale-free network was used and the values for the social parameters were set taking into account previous studies. If data about networking activities were available, more information could be fed into the model. In addition, for future works, the impact of using different levels of subsidies for different groups in the same population could be explored. The use of optimization algorithms could also be studied to identify individuals to drive maximization of the WPT adoption rate in the maritime retrofit industry.

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Authors' contribution

Elena Romero: Software, Data Curation, Validation, Visualization, Writing - Original Draft. **Manuel Chica:** Conceptualization, Methodology, Validation, Writing - Original Draft, Supervision, Funding acquisition. **Roberto Rivas Hermann:** Conceptualization, Methodology, Investigation, Writing - Original Draft. **Sergio Damas:** Validation, Writing – Review editing, Supervision, Funding acquisition.

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