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Synergy of Patent and Open-Source-Driven Sustainable Climate Governance under Green AI: A Case Study of TinyML

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Abstract: Green AI (Artificial Intelligence) and digitalization facilitate the "Dual-Carbon" goal of low-carbon, high-quality economic development. Green AI is moving from "cloud" to "edge" devices like TinyML, which supports devices from cameras to wearables, offering low-power IoT computing. This study attempts to provide a conceptual update of climate and environmental policy in open synergy with proprietary and open-source TinyML technology, and to provide an industry collaborative and policy perspective on the issue, through using differential game models. The results show that patent and open source, as two types of TinyML innovation, can benefit a wide range of low-carbon industries and climate policy coordination. From the case of TinyML, we find that collaboration and sharing can lead to the implementation of green AI, reducing energy consumption and carbon emissions, and helping to fight climate change and protect the environment.

Keywords: climate governance; environmental sustainability; green AI; TinyML; patent; open source

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1. Introduction

Major economies are regaining growth while facing challenges of carbon reduction and environmental protection [1]. Digital wave offers opportunities to achieve the goal of "Dual Carbon" [2], and green AI (Artificial Intelligence) is a tool designed to achieve quality development in a low-carbon economy [3]. As basic research on AI continues to progress [4–7], AI is accelerating from the "cloud" to the "edge" in the fields of smart manufacturing and smart cities [8], into smaller IoT devices for low-carbon energy-efficient computing and public information monitoring [9].

Negative impacts of AI on climate policy include increased electricity consumption and carbon emissions [10], i.e., threats such as cryptocurrencies. A shift to sustainable AI is imperative [3,11,12]. Inclusive, credible, explainable, ethical, and responsible technological approaches are required to drive smart city transformation [13] to mitigate planetary issues in a sustainable manner [13,14].

TinyML (Tiny Machine Learning) supports smart cameras, remote monitoring devices, wearable devices, audio capture hardware, and various sensors [15]. The power consumption and carbon footprint of TinyML devices are much lower than those of cloud computing and ordinary mobile devices, i.e., TinyML devices operate at a MHz level and consume power at a mW level, which is 1000 orders of magnitude lower than cloud computing and mobile devices; CO_2 emission levels are at a kg level, which is one order of magnitude lower.

Undoubtedly, an ecosystem of at least tens of billions of IoT devices will gain machine learning capabilities [16]. Low-carbon and green TinyML can create a healthier and more sustainable environment [17].

We utilize WIPO's PATENTSCOPE database to search for TinyML keywords in searchable fields to obtain relevant patent document information, and we then use crawler software to capture data. We manually referenced IPC code to group, classify, and count these TinyML patents. Second, we retrieve TinyML-related open-source projects from GitHub open-source code hosting platform and organize and classify these open-source projects' programming languages and count them manually. The data in Tables 1 and 2, both sorted in descending order, are obtained through the above acquisition and cleaning process. As the tables show, there are differences in the classification of patent and open source because patent classification focuses more on categorizing inventions as specific technological domains to demonstrate independence and systematic nature [18]. Open-source projects are usually artifacts that depend on each other and other components to build a fully functional system [19], whereas classification of open-source projects repositories is more inclined to functional areas so that developers target and contribute to specific problems or functions.

Table 1. TinyML Patents' IPC Code and Usage Classification Statistics based on WIPO's PATENTSCOPE.

IPC Code	IPC Usage Classification	Count
G06N	computing model	46
G06F	data processing	30
H04L	data transmission	24
G06Q	e-commerce and e-government	19
G06K	data visualization	18
G05B	control system	11
A61B	analytical biology	9
G16Y	IoT communications	8
B25J	robotic arm	6
G06V	computer vision	5
Grand Total		176

Data retrieved as of 1st May 2023.

Table 2. TinyML Open-Source Project Repositories and Artifact Classification Statistics in GitHub.

Programing Language	Artifact Classification	Count
Other (i.e., Assembly, Java, Arduino)	firmware	499
C++	hardware	201
C	hardware	131
Python	software	74
F#	software	14
JavaScript	GUI	10
Go	software	9
HTML	GUI	6
TeX	typesetting	5
Jupyter Notebook	data science	4
CSS	GUI	4
Grand Total		957

Data retrieved as of 1st May 2023.

WIPO patent data (Table 1) indicate that TinyML green AI technology has expected economic benefits in algorithm applications, data processing, control systems, IoT devices, etc. (Figure 1). Open-source data (Table 2) show that repositories related to TinyML in GitHub are mainly distributed in firmware, hardware programming, and algorithm implementation and application at the software level (Figure 2).

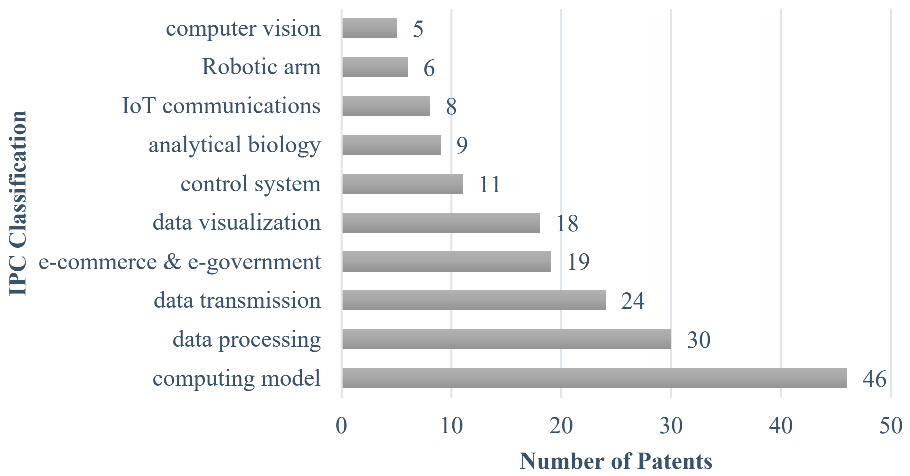

Figure 1. TinyML Green Technology in Patent Innovation Distribution.

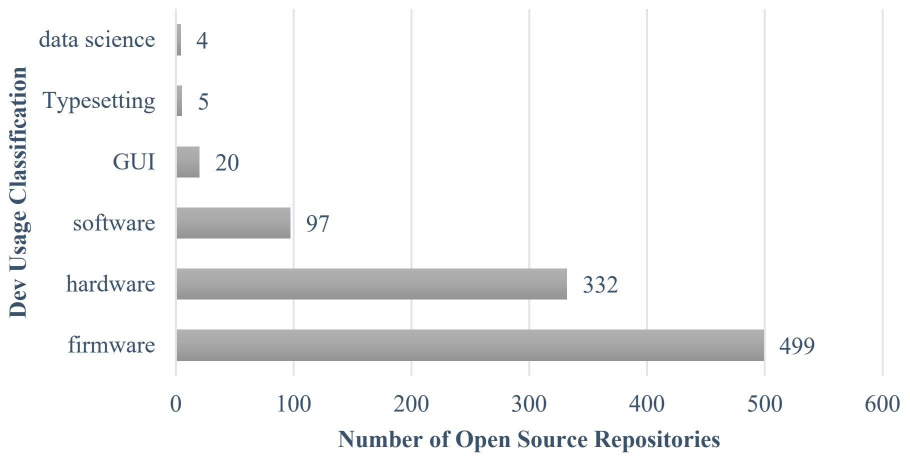

Figure 2. TinyML Green Technology in Open-Source Innovation Distribution.

TinyML's patented and open-source technologies play an essential role in climate policy [20]. Optimizing irrigation for precision agriculture is used to improve crop yield and quality [21,22]. Smart sensing systems are used in the field of early warning and monitoring systems [23,24] to address the challenges posed by natural disasters and climate change [25]. Intelligent energy-management systems reduce energy waste and carbon emissions [26]. In smart cities, optimizing energy use of appliances [27] improves energy efficiency [28] and reduces energy costs [29]. Optimizing traffic flow in intelligent transportation systems reduces traffic congestion and carbon emissions [30]. In conclusion, patented and open-source implementations of TinyML technology can play a positive role in the development of aspects of climate policy.

Patent and open source are two distinct forms of innovation. Knowledge spillovers bring these approaches to innovation closer together [31–33]. Organizations are blending these two approaches to gain advantages in competition [34,35]. Through open-source proactive spillover of technical knowledge, people draw inspiration from existing source code examples or leverage feedback from the community to innovate or improve products [36]. Meanwhile, patent-built barriers are used to protect inventions [37]. In order to form a TinyML green technology cluster, organizations must have both proprietary and open-source technologies. Proprietary technologies create a competitive advantage and bring economic benefits. And open-source technologies facilitate collaboration and expand value networks [38]. Through the synergy of proprietary and open-source technologies, a more efficient and productive cluster can be constructed [39,40].

Research on synergy of patent and open source in TinyML-based green AI is yet to be studied. We try to dissect this issue and also provide a broader vision of industry synergy and policy for the increasingly serious climate and energy challenges.

The significance of this study lies in the fact that it shows the impact of TinyML-based green AI with patent and open-source synergies on climate and environmental governance, and demonstrates the potential to improve efficiency of climate and environmental governance by providing technology-based conceptual updates for low-carbon, green, and sustainable climate policies.

The first section explains the research background, raises research questions, introduces methods, and describes the contributions. The second section discusses related works in recent years that support our study. In the third section, we introduce differential games, showing the results in three situations of noncooperative game, Stackelberg leader–follower game, and cooperative game, and conduct discussions. In the fourth section, we summarize the results of innovative synergy in the areas of proprietary and open source for TinyML low-carbon green technology, and extrapolate to a wider range of low-carbon industries and climate policy collaboration.

Realistic strategic decision-making is a game model that considers time factor and dynamic changes, and differential games provide an analytical approach [41]. Nash's noncooperative game [42] lays the theoretical foundation for differential games, which has become a critical branch of modern game theory and plays crucial role in analyzing competitive strategy, market behavior, and strategic decision-making in economics, management, and engineering [43]. In environmental protection and green AI, patents focus on securing independence of innovative achievements by obtaining economic returns through the granting of patent usage rights. Open source, on the other hand, emphasizes knowledge sharing and collaboration, and promotes the popularization and progress of technological innovation by disclosing the design and source code of innovative achievements. Through differential game analysis of competition conditions, behavioral patterns of participants, and strategic choices and dynamics of competition between patent and open-source approaches are revealed.

The scope of this study includes a conceptual update of climate and environmental policy to incorporate TinyML technology. The analysis covers the potential of TinyML to address low-carbon and climate policy issues through the examination of patent data and open-source data. By using differential game theory to model competition between patent and open-source approaches to environmental protection and low-carbon development, the scope extends to providing an industry collaborative and policy perspective on the issues, with a focus on collaboration, sharing, energy consumption reduction, and carbon emissions reduction for sustainable development in environmental protection.

First, this study makes a marginal contribution to interdisciplinary theories of environmental sustainability and digital innovation: data mining of patent and open source allows for conceptual updates of climate policy and reveals the potential of TinyML-based green AI in balancing environment and efficiency. Secondly, comparing previous works that focus solely on noncooperative [44] or Stackelberg [45] approaches, or on a closed-loop supply chain [46], we examine the application of differential game theory to evaluate complex competing synergistic mechanisms by introducing several key variables and parameters, i.e., rate of open technology value, willingness to open, impact coefficients, decay rates, long-term profits and benefits of combining noncooperative, Stackelberg, and cooperative games, and expanding to industrial competitive synergies.

2. Literature Review

Due to the rapid development of the digital era, smart technologies are seen as an effective tool for solving challenging issues facing the world today and mitigating environmental, social, and economic crises on a global scale [47]. The EU's "Green New Deal" sets out the strategic goal of decoupling economic growth from resource use [48,49]. Industry 4.0 has given rise to the new concept of Cities 4.0 [50], which aims to improve quality of life, productivity, and sustainability of cities with AI [51]. Sustainability profoundly influences the direction of energy, transportation, housing, and agriculture [52]. Green AI advocates a "circular economy" that aims to reduce, reuse, and recycle across sectors and geographies [53]. Thus, the research value of green AI is highlighted. Human capital, financing power, technological innovation, and government policies play critical roles in the green transformation of AI [54]. Patent and open source provide the technical knowledge required to integrate intelligence and greenness [55].

The essence of AI innovation lies in fulfilling efficient and accurate intelligent algorithms [56] to promote humanistic and responsible technological development [57] and social progress [58,59]. Through continuous exploration and improvement of green AI technologies to reduce dependence on natural resources, and multi-disciplinary cooperation and application, people are forging a sustainable [14] intelligent path for the future of human beings and the planet [60]. TinyML [61] implements efficient machine learning models on edge devices with low power consumption and low resource consumption [62], reduces energy dependence, lowers the burden on the environment, which drives green AI technologies, and redefines smart cities [13].

The application and promotion of TinyML is increasing [63]. In recent years, TinyML as a typical technology for green AI is continuously progressing in climate governance, environmental protection, precision agriculture, and smart cities, as demonstrated below.

2.1. In Environmental and Climate Governance

Reducing carbon footprint is crucial. TinyML as green AI is an important tool for realizing climate and environmental policies [29], e.g., overcoming limitations of traditional sensors and monitoring systems [20], superior efficiency and energy saving advantages over traditional machine learning algorithms when running on small devices [64], low power consumption, high efficiency and energy saving capabilities, and low storage costs in environmental radiation-monitoring systems [65,66]. It also offers adaptive unsupervised anomaly detection for extreme environments [67], thus facilitating provision of accurate data for weather forecasting and disaster warnings [68]. The combination of TinyML and CloudML (cloud machine learning) even enhances environmental monitoring and climate prediction [69].

2.2. In Precision Agriculture

TinyML-based green AI addresses key challenges in precision agriculture by providing better tuning of environmental parameters [70], reducing resource consumption [71], improving crop yield and quality [72], and promoting sustainable development. As an example, the TinyML intelligent control system outperforms traditional models in maintaining temperature and humidity balance [73], reducing system response time and resource consumption [74], achieving smarter and more efficient food production [75], reducing energy waste and environmental pollution [76], and thus protecting the environment and mitigating climate change [17].

2.3. In Smart Cities

Industry 4.0 has spawned the new concept of Cities 4.0 [50]. TinyML better realizes the collection and management of urban data. The Intelligent Transportation System (ITS), based on TinyML IoT, can reduce traffic congestion and pollution [71], and promote the green and low-carbon development of smart cities [47,51,77].

2.4. Technological Innovation

TinyML promotes technological innovation through algorithmic optimization. The TinyML algorithm improves energy output efficiency by implementing a Square Cross-section Two-phase Closed heat pump (SCTC) in a photovoltaic (PV) system [78]. TinyReptile, a decentralized edge machine learning model, combines TinyML and coalitional meta-learning to improve computational efficiency and performance [79]. Generalized TinyML benchmarking framework based on different operating system platforms lays the foundation for evaluation [80]. The TinyML compression algorithm reduces memory usage and computational complexity [81], enabling energy-efficient reasoning on Unmanned Aerial Vehicles (UAVs) [28]. The efficiency of the C4.5 decision tree algorithm is improved by determining economic granularity interval in TinyML algorithm optimization [82].

2.5. Competition and Synergy between Proprietary and Open Source

Differences between open source and proprietary have different impacts on the software industry [83] and can be strategically complementary [35] and balanced [84]. Open source and patents have strong synergies [85]. Patents often have a technological lead over open source, but open source can also compete effectively [86]. Patents use a lock-in strategy, while open source offers greater flexibility and freedom [87,88]. Open source is more reliable and secure due to open management and auditing of source code [89,90]. RIVICE (Open Source River Ice Model) demonstrates the benefits of open source in environmental research collaboration and problem solving [91]. Migration timing framework from patents to open source provides strategic guidance [53], and the governance model and platform ecosystem will change [92].

The literature referred to above shows that TinyML's patent and open-source technologies provide additional opportunities for climate governance and environmental protection in multiple areas. Synergy needs to be further investigated.

3. Methods

3.1. Question

In TinyML-based green AI, patent and open source are located at the two ends of the innovation spectrum, with patents bringing economic benefits by establishing technological barriers and open source expanding value networks through proactive knowledge spillovers [31–33], affecting policy on climate and carbon reduction [20]. Patent innovation and open-source innovation form an innovation loop, as shown in Figure 3. The following subsections investigate the open synergy problem of TinyML patent and open source in the context of climate change and carbon reduction through three scenarios: noncooperative game, Stackelberg leader–follower game, cooperative game.

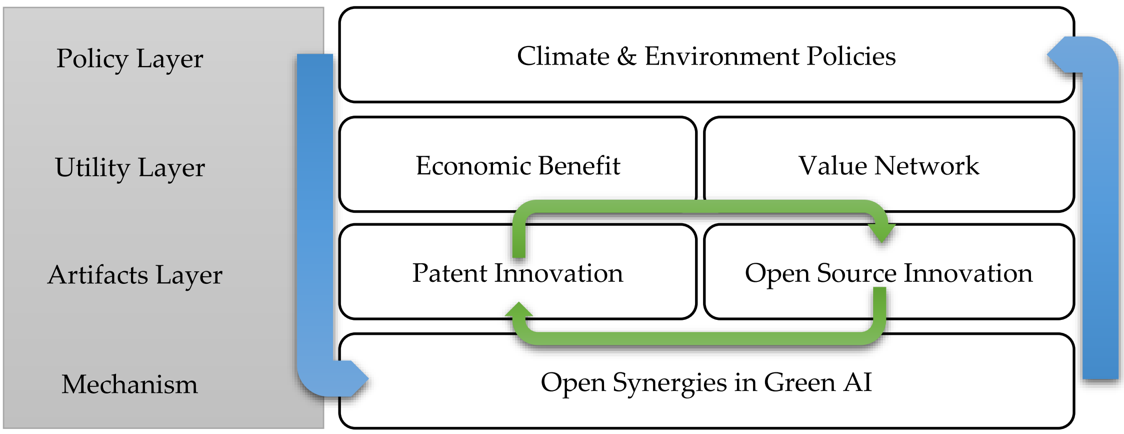

Figure 3. Green Technology Open Synergies for Climate and Environmental Policy Enhancement.

3.2. Premises

Underlying assumption: Proprietary and open-source platforms are participants in this study, both have technological achievements, conform to limited rationality, and make decisions with the goal of maximizing benefits [93]. The cost of technology openness is a convex function of willingness to open up technology [94].

PAPI components: To present differential games, we investigate the Players + Actions + Payoffs + Information (PAPI) framework [95], which reflects dynamic interactions between players' decisions based on the information they observe and the behaviors of others. Competitive synergy is a long-term process with participants' decisions adjusted over time, and they influence each other.

P(Players): Patent platform and open-source platform are participants in this study.

A(Actions): Both players have strategies set {Open, Close} in a discrete view. However, as differential games consider a multidimensional continuum of strategic changes and confrontations [96], players' strategies vary depending on value rate of opening technologies (denoted μ), willingness to open up technology (E), input costs to open up technologies (C), impact coefficient on open synergy effect (λ), decay rate of synergies (δ), marginal return (π), impact factor of technology opening on total return (θ), revenue sharing rate (α), degree of technology openness from patent to open source (σ), discount factor for both platforms (ρ). The relevant symbols are defined in Table 3.

Table 3. Symbols and Description.

Symbol	Description
X	Patent platform
Y	Open-source platform
$\mu_X \in [0,1]$	Value rate of opening up technologies on patent platform
$\mu_Y \in [0,1]$	Value rate of opening up technologies on open-source platform
$E_X(t) \in \mathbb{R}$	Willingness to open up technology on patent platform
$E_Y(t) \in \mathbb{R}$	Willingness to open up technology on open-source platform
$C_X(t) \in \mathbb{R}$	Input costs for patent platform to open up technologies
$C_Y(t) \in \mathbb{R}$	Input costs for open-source platform to open up technologies
$\lambda_X \in [0,1]$	Impact coefficient of patent platform on open synergy effect in TinyML technology
$\lambda_Y \in [0,1]$	Impact coefficient of open-source platform on open synergy effect in TinyML technology
$\delta \in [0,1]$	Decay rate of synergies due to technology opening
$K(t) \in \mathbb{R}$	Synergies from technology opening up at moment t
$\pi_X \in [0,1]$	Marginal return of patent platform
$\pi_Y \in [0,1]$	Marginal return of open-source platform
$\Pi(t) \in \mathbb{R}$	Total return from technology opening
$\theta \in [0,1]$	Impact factor of technology opening up on total return
$\alpha \in [0,1]$	Revenue sharing rate for patent platform
$1-\alpha \in [0,1]$	Revenue sharing rate for open source platform
$\sigma \in [0,1]$	Degree of technology openness from patent platform to open-source platform
$\rho \in [0,1]$	Discount factor for both platforms
$J_X \in \mathbb{R}$	Long-term profits of patent platform
$J_Y \in \mathbb{R}$	Long-term profits of open-source platform
$V_X(K) \in \mathbb{R}$	Benefits from technology opening up on patent platform
$V_Y(K) \in \mathbb{R}$	Benefits from technology opening up on open source platform

P(Payoffs): Payoffs of both players in differential games are measured in terms of their total return from respective strategies. For simplicity, we model interactions by providing a payoffs matrix (Table 4) under three differential game models: noncooperative game, Stackelberg leader–follower game, and cooperative game. The process of equilibrating the games based on HJB equations is given sequentially in Section 3.3.

Table 4. Payoffs under Differential Games.

	Payoffs for Patent Platform	Payoffs for Open-Source Platform
Noncooperative game	V_X^* (10)	V_Y^* (11)
Stackelberg leader–follower game	V_X^{**} (17)	V_Y^{**} (18)
Cooperative game	V_X^{***} (23)	V_Y^{***} (24)

Note: This is a matrix for preview model interactions by both players. Process of equilibrating the games based on HJB equations is given sequentially in Section 3.3.

I(Information):

The patent platform is denoted by X. The value rate of open green AI technology is μ_x. The willingness to open is a time-varying function $E_X(t)$. The input cost by patent platform is denoted as Equation (1).

$$C_X(t) = \frac{\mu_X}{2}[E_X(t)]^2 \tag{1}$$

The open-source platform is denoted by Y. The value rate of open green AI technology is μ_Y. The willingness to open is a time-varying function $E_Y(t)$. The input cost by open-source platform is denoted as Equation (2).

$$C_Y(t) = \frac{\mu_Y}{2}[E_Y(t)]^2 \tag{2}$$

Innovation and technology accumulation of green AI technologies in patent and open-source platforms have a positive incentive effect on technology opening, generating a synergistic effect of technology opening [97], enhancing innovation efficiency of smart green technology industry, and strengthening the policy effect of climate [34].

The synergy effect [98] is a time-varying function [99]. The rate of decay [100] describes decay of synergistic utility over time, given that other variables are equal. λ_X is the influence coefficient, which describes the open synergy effect of the patent platform on TinyML green technology. λ_Y is the influence coefficient, which describes the open synergy effect of the open-source platform on TinyML green technology. δ represents the decay rate of synergies from technology opening. The synergistic effect of technology opening up at time t is denoted as $K(t)$. TinyML's patent and open-source differential equations for generating synergies are as follows:

$$\frac{\partial}{\partial t}K(t) = \lambda_X E_X(t) + \lambda_Y E_Y(t) - \delta K(t) \tag{3}$$

The impact factor of technology openness on total return is denoted as θ. The marginal returns of patent and open-source platforms are π_X and π_Y, respectively. $\Pi(t)$ is the total return of technology openness in the following equation [101].

$$\Pi(t) = \pi_X E_X(t) + \pi_Y E_Y(t) + \theta K(t) \tag{4}$$

The total returns of technology opening are shared between platforms based on rules and mechanisms. The revenue share rate of the patent platform is denoted as $\alpha \in (0,1)$. The revenue share of the open-source platform is $1-\alpha$. Platforms incentivize each other to open up technology. The incentive level is denoted as $\sigma \in [0,1]$ for the patent platform and $1-\sigma$ for the open-source platform. The discount factor is assumed to be positive for both platforms and is denoted as ρ.

Long-term profit functions for two platforms are expressed as follows.

$$\begin{cases} J_X = \int_0^\infty e^{-\rho t}[\alpha\Pi(t) - C_X(t) - \sigma C_Y(t)]dt \\ J_Y = \int_0^\infty e^{-\rho t}[(1-\alpha)\Pi(t) - (1-\sigma)C_Y(t)]dt \end{cases} \tag{5}$$

Symbols used in this section and meanings are listed in Table 3.

The following subsections discuss the results of the two platforms in three game scenarios: noncooperative game, Stackelberg leader–follower game, and cooperative game.

3.3. Game Model

3.3.1. Noncooperative Game

The noncooperative game is the one in which each player has its own interests and goals, and where players do not necessarily need to cooperate with each other to achieve each optimal interest. The patent platform and open-source platform were first regarded as a noncooperative game. Micro and small participants in the patent platform own patented technologies and license or trade them to gain financial benefits. In the open-source platform, developers use and share source codes for free. The open environment creates higher visibility and a greater social effect. Everyone can contribute knowledge and skills, and communicate and collaborate across communities.

In the noncooperative game of the patent and open-source platforms, players make their own decisions and actions to achieve their own optimal interests. In the gaming process, the Nash equilibrium allows us to understand the relationship between cooperation and competition and to find equilibriums.

In the noncooperative game, platforms aim to maximize respective profits and benefits from each technology opening and are a function of synergistic effects, denoted as $V_X(K)$ and $V_Y(K)$, respectively, and satisfy the HJB equation.

$$\rho V_X(K) = \max_{E_X \geq 0}\left[\alpha\Pi(t) - C_X(t) + V_X{}'(k)\frac{\partial}{\partial t}K(t)\right] \tag{6}$$

$$\rho V_Y(K) = \max_{E_Y \geq 0}\left[(1-\alpha)\Pi(t) - C_Y(t) + V_Y{}'(k)\frac{\partial}{\partial t}K(t)\right] \tag{7}$$

By solving the HJB equation, we obtain optimal willingness of each platform to open up its technology and optimal total revenue of each.

$$E_X^* = \frac{\alpha(\pi_X(\rho+\delta) + \theta\lambda_X)}{\mu_X(\rho+\delta)} \tag{8}$$

$$E_Y^* = \frac{(1-\alpha)(\pi_Y(\rho+\delta) + \theta\lambda_Y)}{\mu_Y(\rho+\delta)} \tag{9}$$

$$V_X^*(K) = \frac{\alpha\theta}{\rho+\delta}K + \frac{\alpha^2\mu_X}{2\rho}(E_X^*)^2 + \frac{\alpha\mu_Y}{(1-\alpha)\rho}(E_Y^*)^2 \tag{10}$$

$$V_Y^*(K) = \frac{(1-\alpha)\theta}{\rho+\delta}K + \frac{\alpha\mu_X}{(1-\alpha)}(E_X^*)^2 + \frac{\mu_Y}{2\rho}(E_Y^*)^2 \tag{11}$$

The optimal total benefit (return) is the sum of $V_X^*(K)$ and $V_Y^*(K)$.

$$\begin{aligned} V^*(K) = V_X^*(K) \quad & +V_Y^*(K) \\ & = \tfrac{\theta}{\rho+\delta}K + \tfrac{\alpha(2-\alpha)(\pi_X(\rho+\delta)+\theta\lambda_X)^2}{2\rho\mu_X(\rho+\delta)^2} \\ & + \tfrac{(1-\alpha^2)(\pi_Y(\rho+\delta)+\theta\lambda_Y)^2}{2\rho\mu_Y(\rho+\delta)^2} \end{aligned} \tag{12}$$

3.3.2. Stackelberg Leader–Follower Game

The Stackelberg leader–follower game is noncooperative game model in which players are composed of a leader and a subordinate (or follower). The leader makes the first decision, and the follower makes decisions based on the leader's decision. The leader pre-observes the response of the follower and then makes an optimal decision, while the subordinate needs to follow the leader's decision to make a response. Thus, the leader has the advantage of formulating the best strategy, while the subordinate needs to react to the leader's strategy to achieve the best response.

There is a relationship between technology sharing and competitiveness, and the Stackelberg model helps scholars study the impact of technology sharing on strategies and final market competitiveness [102]. Moreover, part of the Stackelberg game involves technical open sharing between a patent and an open-source platform. Patent holders obtain informational and technological advantages by applying for patents and, therefore, utilize this advantage to formulate optimal strategies. The patent platform effectively controls market pricing and market entry barriers, thus gaining higher profits. The open-source platform, on the other hand, needs to respond to the strategies of the patent platform to maximize resources and technological advantages. The open-source platform utilizes free and open attributes to attract developers and users, providing better user experience and higher-quality products. However, open-source platforms need to comply with patent and intellectual property regulations, and sometimes attempt to circumvent patents [103]. In addition, open-source platforms need to continually innovate and expand the user base to maintain competitive advantages.

In practice, both open-source and patent platforms continually adjust their strategies based on changes in market demand and technological progress. In the Stackelberg leader–follower game, the patent platform acts as leader, while the open-source platform acts as subordinate. Both parties need to continually evaluate market demand and technological trends and formulate corresponding strategies to gain maximum benefits. Assume the degree of technology openness of the patent platform to the open-source platform is $\sigma \in [0,1]$ and the open-source platform follows the decision based on the level of technologies it already possesses.

σ represents the degree of technology openness of the patent platform to the open-source platform. σ takes a value of [0,1], which represents a continuum from no technology openness at all ($\sigma = 0$, no technology is shared) to complete openness ($\sigma = 1$, all technologies are openly shared).

When $\sigma = 0$, patent platform does not open any technology to the open-source platform at all, which means the patent platform completely retains its own technology secrets and does not share any technology with the open-source platform.

When $\sigma = 1$, the patent platform completely opens all technologies to the open-source platform, which means the patent platform is willing to share all technologies with the open-source platform and does not keep any secrets of its technologies.

Benefit from technology openness is a function of synergistic effect from technology openness, denoted as $V_X(K)$ and $V_Y(K)$, respectively, and satisfies the HJB equation. Optimal control of the open-source platform as a follower is described in Equation (13).

$$\rho V_Y(X) = \max_{E_Y \geq 0}\left[(1-\alpha)\Pi(t) - \frac{\mu_X}{2}(1-\sigma)E_Y^2 + V_Y{}'(K)\frac{\partial K(t)}{\partial t}\right] \tag{13}$$

Optimal technology openness intentions for the patent and open-source platforms are as follows.

$$E_X^{**} = \frac{\alpha[(\rho+\delta)\pi_X + \theta\lambda_X]}{(\rho+\delta)\mu_X} \tag{14}$$

$$E_Y^{**} = \frac{(1+\alpha)[(\rho+\delta)\pi_Y + \theta\lambda_Y]}{2\mu_Y(\rho+\delta)} \tag{15}$$

Optimal incentive levels for the patent and open-source platforms are as follows.

$$\sigma^{**} = \begin{cases} \frac{2\alpha-1}{1+\alpha}, \alpha \in (1/3, 1] \\ 0, \alpha \in (0, 1/3] \end{cases} \tag{16}$$

Optimal and total returns for the patent and open-source platforms are as follows.

$$V_X^{**}(K) = \frac{\alpha\theta}{\rho+\delta}K + \frac{\alpha^2[(\rho+\delta)\pi_X + \theta\lambda_X]^2}{2\rho\mu_X(\rho+\delta)^2} + \frac{(1+\alpha)^2[(\rho+\delta)\pi_Y + \theta\lambda_Y]^2}{8\rho\mu_Y(\rho+\delta)^2} \tag{17}$$

$$V_Y^{**}(K) = \frac{(1-\alpha)\theta}{\rho+\delta}K + \frac{\alpha(1-\alpha)[(\rho+\delta)\pi_X + \theta\lambda_X]^2}{\rho\mu_X(\rho+\delta)^2} + \frac{(1-\alpha^2)[(\rho+\delta)\pi_Y + \theta\lambda_Y]^2}{4\rho\mu_Y(\rho+\delta)^2} \tag{18}$$

$$V^{**}(K) = V_X^{**}(K) + V_Y^{**}(K) = \frac{\theta}{\rho+\delta}K + \frac{\alpha(1-\alpha/2)[(\rho+\delta)\pi_X + \theta\lambda_X]^2}{\rho\mu_X(\rho+\delta)^2} + \frac{\frac{1}{2}(3-2\alpha+3\alpha^2)[(\rho+\delta)\pi_Y + \theta\lambda_Y]^2}{\rho\mu_Y(\rho+\delta)^2} \tag{19}$$

Using the patent platform as leader, as described above, can be extrapolated to, e.g., a small patent firm (SPF) or a small open-source firm (SOSF). (1) If the SPF acts as leader, it seeks patent protection more aggressively to ensure exclusivity and market dominance of its innovations in order to maintain inflow of economic benefits and operational sustainability. The SPF adopts more conservative strategies to control the release and sharing of intellectual property to protect its interests. (2) If the SOSF acts as leader, it should emphasize open-source innovation and collaboration, and share knowledge and source code with other developers and researchers. This promotes technological progress and market development while increasing influence and competitiveness. Open-source developing lends itself to large-scale collaboration and sharing, thus posing a significant challenge to the SOSF with limited resources. In brief, small firms tend to face constraints in terms of resources and size in highly competitive markets. Industrial centrality of innovations, flexibility of innovation, and diversity of innovation cooperation networks are crucial for becoming a leader. Both open-source and patent small firms need appropriate strategies based on resources and goals, and adapt to a competitive environment and market changes.

3.3.3. Cooperative Game

The cooperative game is one in which players make decisions with the goal of maximizing common interests. Sometimes, all players maximize their gains, while at other times, one player needs to lose its benefits to maximize collective benefits, thus maximizing sustainability of cooperation. A cooperative game of technology openness is a way to achieve a mutually beneficial situation through open technology. In the technology openness scenario, various players cooperate through technology sharing and knowledge transfer [104], i.e., patent platform facilitates exchange data and innovation through open data sharing. Data providers and users collaborate to achieve appropriate data usage. Patent owners use the open-source platform to allow more users to use and submit contributions, increasing the stability and functionality of the technology, as well.

The patent platform and open-source platform allocate total benefits obtained from the cooperative game of technology opening at a rate of $\alpha \in [0,1]$ for the patent platform and $1-\alpha$ for the open-source platform. Revenues as total benefits received by the patent platform and open-source platform are based on technology openness allocation. When $\alpha = 0$, the patent platform receives zero benefits and all benefits are retained in the open-source platform, which means that the patent platform fully opens up its technology and is willing to give up its own financial interests for the development of an open-source community. When $\alpha = 1$, the open-source platform gains zero benefits and all benefits go to the patent platform, which means that the patent platform fully retains revenues and shares no technology with the open-source platform. The value of α can be determined according to the interests and goals of both parties to the cooperation, and it is an adjustable parameter that can regulate the distribution of benefits in the cooperation agreement.

Benefits of technology opening for both players are denoted as $V_X(K)$ and $V_Y(K)$, and total benefits are denoted as $V(K)$, and both satisfy the HJB equation.

$$\rho V(K) = \max_{E_X \geq 0, E_Y \geq 0} \left[\Pi(t) - \frac{\mu_X}{2} E_X^2 - \frac{\mu_Y}{2} E_Y^2 + V'(K) \frac{\partial}{\partial t} K(t) \right] \tag{20}$$

Open intentions for the patent and open-source platforms are as follows.

$$E_X^{***} = \frac{(\rho+\delta)\pi_X + \theta\lambda_X}{(\rho+\delta)\mu_X} \tag{21}$$

$$E_Y^{***} = \frac{(\rho+\delta)\pi_Y + \theta\lambda_Y}{(\rho+\delta)\mu_Y} \tag{22}$$

Optimal returns and optimal total return from open technology for both players are as follows.

$$V_X^{***} = \frac{\alpha\theta}{\rho+\delta}K + \frac{\alpha[(\rho+\delta)\pi_X + \theta\lambda_X]^2}{2\rho\mu_X(\rho+\delta)^2} + \frac{\alpha[(\rho+\delta)\pi_X + \theta\lambda_Y]^2}{2\rho\mu_Y(\rho+\delta)^2} \quad (23)$$

$$V_Y^{***} = \frac{(1-\alpha)\theta}{\rho+\delta}K + \frac{(1-\alpha)[(\rho+\delta)\pi_X + \theta\lambda_X]^2}{2\rho\mu_X(\rho+\delta)^2} + \frac{(1-\alpha)[(\rho+\delta)\pi_X + \theta\lambda_Y]^2}{2\rho\mu_Y(\rho+\delta)^2} \quad (24)$$

$$V^{***} = \frac{\theta}{\rho+\delta}K + \frac{[(\rho+\delta)\pi_Y]^2}{2\rho\mu_X(\rho+\delta)^2} + \frac{[(\rho+\delta)\pi_Y + \theta\lambda_Y]^2}{2\rho\mu_Y(\rho+\delta)^2} \quad (25)$$

The cooperative game on technology open scenarios is an important method of cooperation between enterprises, which promotes technological innovation and market competitiveness. Through the cooperative game of technology openness, enterprises mutually promote each other, develop together, and form a strong joint competitiveness, and also make positive contributions to the industry. The following section discusses the noncooperative game, Stackelberg leader–follower game, and cooperative game between patent and open source.

4. Discussion

4.1. Results Analysis

A numerical example is provided based on definitional and value domains in Table 1 in Section 3.2, by randomly selecting values for these variables and parameters:

$\alpha = 0.4, \theta = 0.3, \delta = 0.2, \rho = 0.2, \mu_X = 0.3, \mu_Y = 0.4, \lambda_X = 0.2, \lambda_Y = 0.3, \pi_X = 0.5,$ $\pi_Y = 0.6$, and $K(t=0) = 2$, outcomes on willingness to open up technology (denoted E) for both players separately are obtained as $E_X^* \approx 0.8667 \leq E_X^{**} \approx 0.8667 < E_X^{***} \approx 2.1667$, and $E_Y^* \approx 1.2375 < E_Y^{**} \approx 1.4438 < E_Y^{***} \approx 2.0625$. It can be seen that the willingness to open up of both players increases progressively under the three types of games.

Further, benefits from technology opening (denoted V) for both players separately are obtained as $V_X^* \approx 3.20521 < V_X^{**} \approx 3.24775 < V_X^{***} \approx 3.7099$, and $V_Y^* \approx 4.12141 < V_Y^{**} \approx 4.37664 > V_Y^{***} \approx 4.29734$. It can be seen that the benefit of the patent platform is strictly partial order with Pareto improvement under three games. Benefits of the open-source platform are not strictly partial order, and the open-source platform has the highest benefit (denoted V_Y^{**}) as the follower role under the Stackelberg leader-follower game.

In addition, from patent and open-source platforms' synergistic view, the total benefit (return) denoted as V is obtained as $V^* \approx 7.32661 < V^{**} \approx 7.62439 < V^{***} \approx 8.00724$, which is strictly partial order with Pareto improvement.

The results and numerical data above show that the total benefits of both platforms are Pareto improvement under the three games and having Pareto optimality under synergy (Figure 4). The platform's intention to cooperate under the Stackelberg leader–follower game increases with the level of incentive for technology openness input, which is related to the design of the incentive mechanism. Both parties have a higher willingness to open up technology under the cooperative game than under the noncooperative game. Attitudes and behaviors towards technology openness are not stable but can be influenced by various factors. Intention to open up technology is higher under the cooperative game than the noncooperative game, which indicates that mutual collaboration and exchange tend to foster innovation, resulting in better technology and higher returns [105]. Therefore, when making technology opening decisions, companies should take these influencing factors into account, combine them with the actual situation, and make a more effective technology opening strategy to achieve better competitive advantage and business returns.

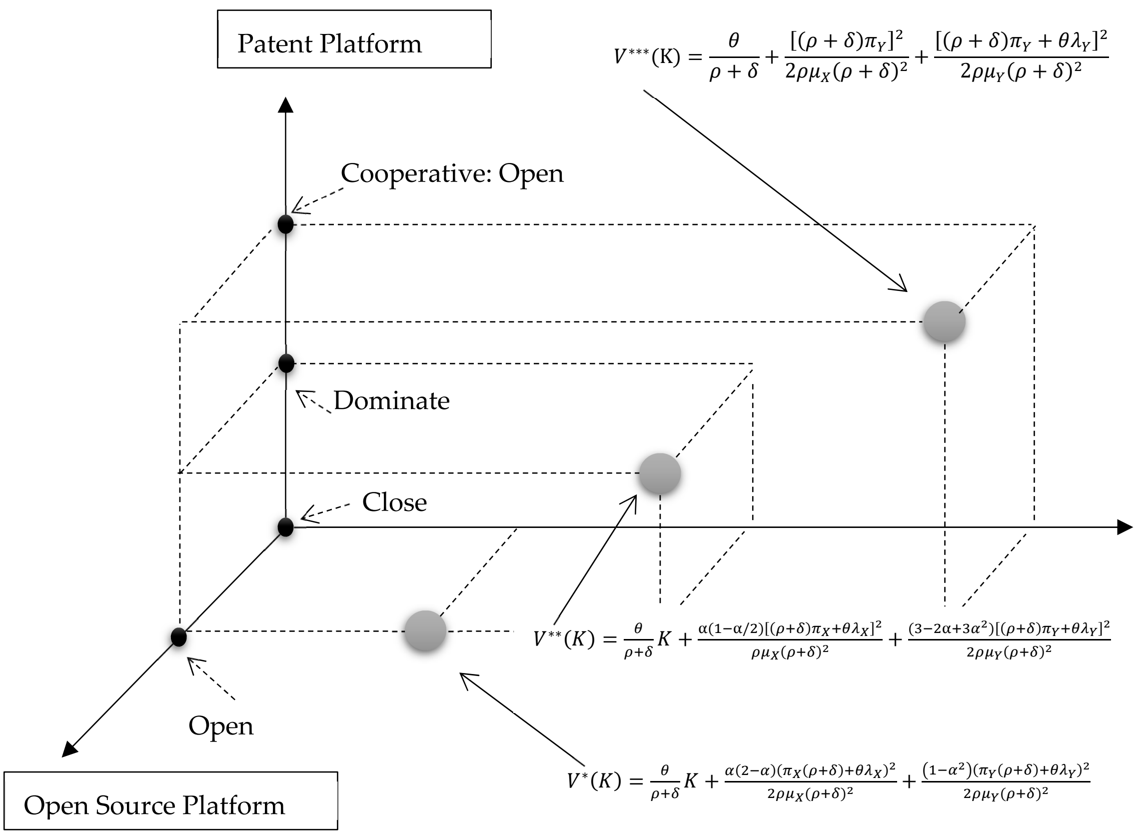

Figure 4. Level of total return for different strategy combinations.

(1) In the noncooperative game, in addition to considering changes in the willingness to open up technology, it is also necessary to consider the conflict of interest and incentives for noncooperation of the parties, including the effects of competition and uncertainty in the external market, resource allocation, and risk taking [106]. Strategies that can reduce incentives for noncooperation and conflicts of interest are formulated to achieve a better competitive advantage.

(2) In the Stackelberg leader–follower game, in addition to the level of incentives for technology openness, it is also necessary to analyze how much influence and control the leader has over the follower, as well as how much the follower trusts the leader and how receptive they are to technology openness decisions [107]. As mentioned in Section 3.3.2, role swapping between leader and follower is also an aspect worth investigating, i.e., when open-source platforms have sufficient core technology resources, the follower becomes the leader and has a dominant influence on the technology opening of the industry cluster [108]. Open-source platforms need to invest resources and incentives in order to encourage more developers and enterprises to join in technology sharing and innovation [109]. Meanwhile, the design of incentives for open-source platforms also needs to take into account the specificity and needs of the industry to establish a more flexible and effective mechanism for technological innovation [110]. Therefore, exploring the influence of power structure and role transformation on the willingness of technology openness in the Stackelberg leader–follower game is of great significance for enterprises when formulating technology openness strategies.

(3) In the cooperative game, strong willingness to open up technology and synergy between patent and open source has a boosting effect on innovation and returns. Sharing can bring mutual trust and cooperation, which leads to a greater market share and improved market competitiveness [111]. In the cooperative game, both players have higher trust and willingness to cooperate, which provides a more positive environment for technology opening. In addition, cooperation can also provide

more sharing of resources and expertise, which further promotes the development and innovation of technology [112]. Therefore, when enterprises make decisions on technology opening, they can consider establishing a stable cooperative game model through partnership, cooperative research and development, or technology sharing in order to achieve better results of technology opening [113].

The analysis above is insightful. Firms and policymakers should recognize the benefits of technology sharing and synergy in green AI industry. Firms should promote technology openness and incentivize collaboration while also protecting their own intellectual property rights. Policymakers should develop flexible laws and policies that encourage technology sharing and innovation while also promoting industrial upgrading and economic growth. Additionally, enterprises should strive for balance and caution in technology openness to protect their core technologies while engaging in healthy competition and collaboration with others. By adopting synergy, the TinyML-based green AI industry can achieve sustainable development and competitive advantages.

4.2. Synergistic Approach

Current climate and environmental governance policies should seek to actively engage with both patent and open-source areas of TinyML, promoting technology openness and innovative synergies between platforms. The following approaches are suggested.

(1) Promote the collaborative development of proprietary and open-source TinyML for climate and environmental governance goals. Use patent and open source together to develop TinyML components. This approach combines the advantages of patent and open source to ensure that TinyML development aligns with climate and environmental goals while remaining competitive and adaptable. Open patenting, a model that emphasizes knowledge sharing and collaboration, allows for technology sharing and licensing, fostering innovation and industrial progress [114]. Open patents can be a collective intelligence solution to drive technological innovation and adoption.

Under TinyML's climate and environmental governance objectives, open patents and open source can play a synergistic role in promoting the collaborative development of proprietary and open-source technologies [115].

In terms of open patent usage, proprietary technology companies can open up some of their patents to allow the open-source community to use them in their own projects, which can allow the open-source community to gain access to the application and technology experience of proprietary technology companies and build on it for better innovation.

In terms of building open-source frameworks, know-how companies can release their own products based on open-source frameworks, i.e., the open-source community, which can allow more developers to participate in the development of that product and ultimately create more solutions.

In terms of promoting co-development: proprietary technology companies and open-source communities can work together to develop new TinyML applications and share technology through open source, promoting continuous innovation in technology while learning from each other's experiences.

In terms of establishing a technology sharing platform, know-how companies can provide effective support for the open-source community in terms of know-how through a technology sharing platform with a focus on exchanging technology and reaching consensus on sharing technology experience, intellectual property, and patents, thereby creating more business opportunities.

(2) Foster co-promotion of proprietary and open-source TinyML under climate and environmental governance objectives. Proprietary and open-source platforms can work together to promote the use of TinyML technology. Patent and open-source platforms can collaborate to promote the use of TinyML technology. Open-source platforms can raise awareness and popularity by involving more developers in open-source hardware and software. Proprietary technologies can be applied to a wider range of fields through licensing agreements [116]. Collaboration among enterprises, organizations, and industry

groups can drive the development and application of TinyML technology in various sectors like smart agriculture and environmental protection. Strengthening the open-source community can enhance the dissemination and promotion of open-source technology. Active participation in policy and standard formulation can further enhance the role of TinyML technology in environmental governance and protection. Leveraging media, conferences, and forums can increase public awareness and understanding, promoting the development and application of TinyML technology in environmental governance and protection.

(3) Facilitate cross-fertilization of proprietary and open-source TinyML in the context of climate and environmental governance objectives. Patent and open-source technologies can collaborate to enhance the quality and efficiency of TinyML technology [117]. Open innovation can enable the joint development of new applications, allowing for knowledge exchange and improvement of technical expertise and effectiveness. Technical exchanges through conferences and forums can facilitate sharing of experiences and cases to advance TinyML. Establishing a talent training system can provide excellent professionals for both the open-source community and proprietary technology enterprises, promoting technology development and application. Collaboration in standardization efforts can better promote and implement TinyML standards. Creating a sharing platform for small, low-cost, and low-power TinyML devices can enable practitioners to share their experiences and learn from each other, enhancing the overall effectiveness of the technology.

In summary, promoting the mutual learning of proprietary and open-source TinyML in the context of climate and environmental governance objectives requires the open-source community and proprietary technology companies to work together to promote technology development and application, and to make a concerted effort in open innovation, technology exchange, talent training, standardization, and common sharing. In these ways, patented and open-source technologies can synergize and encourage each other to higher achievements and better results in the development of TinyML technology [88].

5. Conclusions

TinyML is machine learning based on small machine learning algorithms, low power consumption, low cost, and small data sets. Compared to conventional machine learning algorithms, TinyML's algorithms are designed to run on low-power devices such as IoT, portable devices, and drones. However, there may be competition between the two models of TinyML, proprietary and open source, which could be detrimental to the low-power IoT industry and climate environmental policy. In particular, in terms of patents, if technological innovation is blocked, then the industry will be stuck with a monopoly of knowledge and an inability to innovate. Especially in a highly specialized field such as TinyML, whether patents can be managed properly will directly affect industry costs, market competition, and the speed of industry innovation. The sustainability of the industry's development may also be affected if it relies only on open source.

As open source and patent technologies spread, this double-sided character intensifies. Which is more critical for green AI, open source or patented innovation roles? Open source freely discloses source code to the public to boost collaboration and joint improvement. In contrast, patent protects intellectual property and exclusive ownership. In the context of green AI, i.e., TinyML, where the focus should be on environmental friendliness, compared to high-energy consumption and pollution of traditional AI, which means both should contribute to the development and deployment of green AI solutions. Open-source innovation can foster collaboration and knowledge sharing among researchers and developers, leading to faster and wider development of AI technologies with environmentally friendly properties. Through open source, developers can improve on existing solutions, increasing efficiency and reducing environmental impact. On the other hand, patent innovation can encourage companies in green AI technological investment. Patents offer the right to protect inventions and realize innovations, which can drive commercialization and scaling of green AI solutions. Ultimately, open source and patent strike a balance. Open source can drive initial research and development of green AI, while patents can provide companies with the financial incentives necessary to bring technologies to market at scale. In brief, while open source and patent are critical in any technological advancement, they should be balanced with a focus on environmentally friendly use in green AI. A combination of open-source collaboration and patent protection can drive development and deployment of sustainable AI solutions that mitigate the effects of climate change.

First, this study makes a marginal contribution to interdisciplinary theories of environmental sustainability and digital innovation which provides a conceptual update of climate policy with the potential for TinyML-based green AI to balance environment and efficiency; second, this study contributes by applying differential game theory to evaluate complex competing synergistic mechanisms by introducing several key variables and parameters with combining noncooperative, Stackelberg, and cooperative games and expanding to industrial competitive synergies.

This study's limitations lie in a relatively novel direction with lag in disclosure of practice and research. Furthermore, as climate and environmental research is often related to ethical and sustainability issues, limitations such as data privacy, energy consumption, and environmental protection need to be carefully considered when applying TinyML technology.

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