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EDITED BY
Pierre Glynn,
United States Geological Survey (USGS),
United States

REVIEWED BY
Jihong Chen,
Shenzhen University, China
Zhengmao Li,
Aalto University, Finland

*CORRESPONDENCE
Duo Zhang,
zhangduosjz@163.com

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Integrating coevolutionary strategies and risk preferences: a novel supervision insight for pollutant abatement

Xiaonan Wang[1] and Duo Zhang[2]*

[1]School of Management, Northwestern Polytechnical University, Xi'an, China, [2]School of Management, Shenyang Jianzhu University, Shenyang, China

The importance of pollutant abatement has been steadily growing in recent times, prompting an increased focus on developing effective regulatory mechanisms. This paper introduces a novel approach by combining theories of evolutionary games and opinion dynamics to formulate a coevolution model of game and preference. Recognizing the challenges posed by limited supervision ability and enterprises' heterogeneous risk preferences, we propose a smart supervision mechanism. This mechanism incorporates the concepts of whitelist capability and observation period to establish intelligent supervision. Simulation results demonstrate the regulator's ability to accurately discern enterprises' preferences based on decision-making differences. The smart supervision mechanism proves to be more effective in achieving pollutant abatement goals compared to random supervision. Furthermore, our findings indicate that with higher supervision ability, increasing whitelist capability enhances cooperation rates. Conversely, lower supervision ability necessitates a shorter observation period and increased whitelist capability to achieve optimal pollutant abatement results. The study highlights that enterprises with a high cooperation rate experience more significant benefits, while risk-seeking enterprises benefit less due to heightened regulator attention at the same cooperation rate.

KEYWORDS

pollutant abatement, risk preference, evolutionary game, opinion dynamics, supervision mechanism

1 Introduction

The industrialization process leads to a significant surge in pollutant emissions, particularly pronounced in developing countries (Carraro and Sgobbi, 2008). This surge in pollutant emissions contributes to a myriad of issues encompassing environmental, healthcare, and social concerns (Wang and Yang, 2016). Consequently, addressing pollutant emissions becomes an imperative matter. Various approaches to achieve pollutant abatement have been explored. Globally, certain environmental organizations are dedicated to funding initiatives aimed at reducing pollution and promoting global sustainable development. However, these efforts often lack mandatory mechanisms. On a regional governmental level, pollutant abatement is enforced by government regulators through the imposition of punitive taxes or the closure of non-compliant enterprises (Wu et al., 2020).

Evolutionary game theory has emerged as a prominent framework in recent years for studying pollutant abatement, offering a powerful tool to analyze the dynamics between regulators and enterprises (Xu et al., 2021; Gu et al., 2022; Ning et al., 2022). This paper aims to delve into the practical application of evolutionary game theory in the context of pollutant reduction, specifically examining how businesses evolve their cooperative strategies in the face of collective risks, with a particular focus on navigating the societal dilemma between economic interests and environmental protection. By synthesizing supporting literature, we will conduct an in-depth exploration of the tangible impacts of evolutionary game theory in addressing the complex interactions between regulatory agencies and businesses. The study seeks to unveil the potential contributions of evolutionary game theory in propelling more effective and sustainable solutions for pollutant abatement, providing novel insights for future research endeavors.

The system of regional pollutant abatement contains regulators and a bunch of enterprises. In this system, enterprises cooperate on pollutant abatement with regulators' supervision under collective risk (Liu et al., 2023; Yu et al., 2023; Zeng et al., 2023). Enterprises, especially energy-intensive ones, are the central responsible bodies of pollutant emissions. However, enterprises put the economic benefits in a more critical position than environmental protection (Bahel, 2018). Achieving more economic benefits requires higher consumption of resources leading to more pollutant emissions, which is a social dilemma putting back cooperation willingness of pollutant abatement (Chen et al., 2014). Due to the lack of supervision, the failure of pollutant abatement occurs in some regions, making human beings suffer from environmental deterioration (Vasconcelos et al., 2014). To some extent, regulators' supervision promotes enterprises' pollutant abatement (Liu and Li, 2019). Common supervision ways include rewarding and punishing (Wang et al., 2010; Jeon et al., 2015; Wang and Shi, 2019). However, it is hard for regulators to supervise all enterprises in the region considering the supervision ability. In the absence of supervision, some enterprises may take risks to emit pollutants lured by higher benefits (Xu et al., 2019). Thus, achieving a better effect under limited supervision ability is a valuable research issue.

In reality, different enterprises have heterogeneous opinions or attitudes, namely, preferences, towards pollutant abatement. Some enterprises prefer abating pollution to avoid punishment, and others prefer adopting a non-abatement strategy for potentially higher benefits when regulators fail to supervise them. The hypothesis of bounded rationality holds that decision-makers cannot make completely rational decisions when facing complex problems due to incomplete information, inconsistent preferences, and limited cognitive ability (Di and Liu, 2016). Moreover, due to the influence of the social environment, enterprises' preferences may change (Acemoglu and Ozdaglar, 2011). Opinion dynamics hold that others influence an agent's opinion in the system. Agents may change their opinions by comparing with other agents' performance (Mäs et al., 2010). As a result, both enterprises' strategies and preferences coevolve in pollutant abatement games. Besides, heterogeneous risk preferences cause behavior differences between enterprises. Regulators should consider the heterogeneous risk preferences when selecting supervised enterprises. Thus, a new supervision mechanism is proposed considering the limited supervision ability and heterogeneous risk preference.

The main contributions of this paper are as follows. First, we consider the enterprises' preference evolution of pollutant abatement based on opinion dynamics. The coevolution of game and preference runs synchronously. This innovation assists regulators in supervising enterprises pertinently according to the agents' heterogeneous preferences. Thus, our approach promises to complement the research on pollution control in the case of bounded rationality. Second, we propose a smart supervision mechanism considering heterogeneous risk preference and limited supervision ability and compare the effect of the smart supervision mechanism with the random supervision mechanism: 1) regulators supervise enterprises randomly under the random supervision mechanism; 2) regulators mainly supervise enterprises with a negative attitude towards pollutant abatement under the smart supervision mechanism. Thus, this paper provides new insight into reforming the supervision mechanism to achieve a better abatement effect.

The remainder of this paper is organized as follows. The next section reviews the literature on supervision and preference. In Section 3, we construct the game model for pollutant abatement with two different supervision mechanisms based on preference evolution. Then, Section 4 explores and compares two different supervision mechanisms under different supervision abilities by simulations. In Section 5, we give conclusions and discuss policy recommendations and limitations.

2 Literature review

2.1 Punishment and supervision mechanism

The evolutionary game is a standard tool for studying social dilemmas. The issue of pollutant abatement involving regulators and enterprises using evolutionary game theory has been explored recently (Zu et al., 2018; Wang and Shi, 2019; Zhang et al., 2019; Kou et al., 2021; Zhou et al., 2022). Enterprises select the abatement or non-abatement considering benefits maximization and the risk of punishment (Chang et al., 2015). More recent works studied the threshold public goods game (TPGG) by increasing the collective risk to promote cooperation. In TPGG, enterprises need to achieve common goals to avoid collective risk (Santos and Pacheco, 2011; Tavoni et al., 2011). However, maximizing self-benefits is contrary to common goals, which causes the collapse of cooperation. Thus, punishment is introduced to the TPGG model, and enterprises cooperate to avoid potential losses caused by punishment (Barrett, 2013; Schmidt, 2017).

Some research discusses the enterprises' strategy selection given the punishment (Zu et al., 2018; Wang and Shi, 2019). For example, Gupta et al. investigated the relationship between environmental protection supervision and factory compliance in developing countries, and proved that supervision and factory pollution discharge are interrelated (Gupta et al., 2019). Under the punishment, Jiao et al. considered an evolutionary game between governments and enterprises with carbon emission constraints. Moreover, some research discusses enterprises' reactions towards different punishment methods (Jiao et al., 2017). Common forms of punishment include punitive tax, fining, and even shutdown. For example, considering static and dynamic punishment, Wang and Shi constructed an evolutionary game model of industrial pollution between local government and enterprises (Wang and Shi, 2019).

Punishment is a critical method of regulators' supervision. Recent studies focus on punishment methods considering collective risk and risk preferences, such as collective fining and random fining (Alpízar et al., 2004; Camacho-Cuena and Requate, 2012). Under collective fining, regulators punish the whole polluters if the pollutant emission exceeds the level set by regulators. In contrast, one potential polluter is chosen randomly under random fining, irrespective of being one of the actual polluters. For example, Alpízar et al. presented an experimental study of two different punishment methods: collective and random fining to supervise pollution behavior (Alpízar et al., 2004). Camacho-Cuena and Requate proposed an experimental study including random fining and collective fining considering risk preferences, and the result showed that risk-seeking agents worsen the effect of pollutant abatement (Camacho-Cuena and Requate, 2012). However, the above punishment methods have some deficiencies. First, collective fining does not consider the limited supervision ability and the difficulty of the actual implementation. Second, random fining is hard to optimize the limited supervision resources due to the lack of supervision pertinence.

Some supervision mechanisms based on various factors have been proposed. Fan et al. proposed three supervision strategies for enterprises that apply for subsidies considering the supervision cost (Fan et al., 2017). Xu et al. built an evolutionary game model of third-party supervision, including governments, environmental services companies, and pollutant enterprises, to analyze the effect of critical factors on cooperation (Xu et al., 2019). However, little research is related to optimizing supervision mechanisms under limited supervision ability. Besides, in earlier research, the literature on pollutant emission reduction regulatory mechanisms initiated a preliminary exploration, proposing the concept of supervising agents based on heterogeneous risk preferences under the assumption of limited supervisory ability (Wang et al., 2023). However, these prior studies primarily focused on evolutionary game theory and complex network theory, concentrating on the optimization of regulatory mechanisms while neglecting the influence of the evolution of risk preferences on strategic choices. In comparison, our study emphasizes the application of evolutionary game theory and opinion dynamics, with a specific focus on the evolving risk preferences of enterprises during the game. Simultaneously, this research addresses some gaps present in previous studies by introducing opinion dynamics and the coevolution of strategies and preferences.

Our study is concentrated on revealing how strategies and preferences coevolve in enterprise decision-making. Through the lens of opinion dynamics, we offer a distinctive analytical perspective that accentuates the dynamic processes underlying individual decision-making in the game, thereby expanding our comprehension of pollutant emission reduction regulatory mechanisms.

2.2 Preference evolution

The hypothesis of bounded rationality holds that there are no completely rational decision-makers manifesting as bounded rationality in decision-makers' preferences (Camerer, 1997; Di and Liu, 2016). Camerer proposed and introduced social preferences into the game theory (Camerer, 1997). Social preferences have been used to explore complex system issues about social dilemmas, such as fair preference (Fan et al., 2017), reciprocal preference (Wu, 2014), and altruistic preference (Fan et al., 2019). Risk preferences demonstrate enterprises' attitudes towards the potential risk, including risk-averse (RA), risk-neutral (RN), and risk-seeking (RS) (Camacho-Cuena and Requate, 2012; Larue et al., 2017). RA agents prefer a safe strategy to avoid losses caused by potential risks, while RS agents, on the contrary, prefer an adventurous strategy for higher profits. Bontems and Nauges considered a model of pollution supervision for RA agents involving hidden information and moral hazard (Bontems and Nauges, 2019). Camacho-Cuena and Requate proposed three supervision mechanisms, including collective fining, random fining, and a tax-subsidy scheme, and compared the strategy selection of RA and RS enterprises under different supervision mechanisms (Camacho-Cuena and Requate, 2012).

Two aspects have been rarely explored in the aforementioned studies. First, agents in a complex system could be a multi-preference group. Different agents have heterogeneous preferences. For example, by introducing social preference, Chen et al. divided the preferences of Internet users into egoistic, altruistic, and fair preferences (Chen et al., 2020). They studied the effects of different social preferences on public opinion. Second, social preferences are static in most previous studies, but the preferences could be dynamic over time. Agents' preferences could be influenced by interacting in the system and change in the evolutionary game process. Variability in the external environment might affect agents' decisions and force a change in agents' preferences. The theory of opinion dynamics is a new approach to simulating dynamic preference evolution (Acemoglu and Ozdaglar, 2011; Axsen et al., 2013; Liang et al., 2019; Chen et al., 2020). Axsen et al., for example, investigated the roles of social influence in the formation of consumer preferences for pro-environment technologies, and the result showed that preferences change through social interaction (Axsen et al., 2013). The effect of preference evolution on social cooperation is underestimated.

The theory of opinion dynamics is a powerful tool for describing an interactive group and exploring preference evolution (Liang et al., 2019; Zhang et al., 2019). Opinion denotes the agents' views or attitudes in opinion dynamics (Chen et al., 2023). The Hegselmann and Klause model (HK model) is one of the original opinion dynamics models (Hegselmann and Krause, 2002). In the HK model, opinions are described as real numbers in a fixed interval, and agents interact with each other if their opinions are similar. Agents update their opinions by averaging all similar opinions within the confidence threshold at each discrete time. There are variously improved models based on the original HK model (Fu et al., 2015; Han et al., 2019). In a modified HK model, agents update opinions considering the game payoff (Bauso and Cannon, 2018). Motivated by the above research, this paper introduces a preference evolution model considering the weight based on the game payoff.

Combined with opinion dynamics, some studies on preference evolution involve social issues. Liang et al. argued that preferences would be dynamically evolved and developed a preference evolution model based on online interactions through a communication tool (Liang et al., 2019). The research of preference evolution focuses on a social complex system, but the problem of pollutant abatement with preference evolution is yet to be explored. Therefore, we introduce the theory of opinion dynamics to fill the gap in the study of pollutant abatement among regional enterprises with preference evolution.

3 Model

First, we introduce a preference evolution model using the opinion dynamics theory. Next, we propose an evolutionary game model for pollutant abatement involving regulators and enterprises. Simultaneously, we develop a smart supervision mechanism based on the random supervision mechanism to reduce pollutant emissions.

3.1 Preference evolution of enterprises

After each game, agents update their preferences synchronously considering benefits. If an enterprise has a higher benefit at this time, the enterprise has a strong impact on others' preferences.

We consider a population composed of N enterprises. The preference of enterprise i at discrete time t is described by $x_i(t)$. In the initial state, preferences of all enterprises on pollutant abatement are uniform distribution in the range of [-0.5, 0.5]. If $x_i(t) < 0$, agent i has a preference for RA. On the contrary, if $x_i(t) > 0$, agent i has the preference for RS. Likewise, if $x_i(t) = 0$, agent i is RN and selects strategy only according to the benefit comparison. Besides, the greater the absolute value of $x_i(t)$ is, the stronger the preference degree is. In the original HK model, ε is the bounded confidence. Agent i interacts with agent j if $|x_i(t) - x_j(t)| \le \varepsilon$ and $i \ne j$ (Hegselmann and Krause, 2002). Meanwhile, agent j is a neighbor of agent i. An agent updates preference by averaging its and its all neighbors' preferences, written as

$$x_i(t+1) = \frac{\sum_{j\in N_i(t)} x_j(t)}{\|N_i(t)\| + 1}. \tag{1}$$

where $N_i(t)$ denotes the set of agents interacting with agent i at time t, and $\|N_i(t)\|$ is the members' number of $N_i(t)$.

We consider a modified HK model to depict preference evolution. In the modified model, each preference has a weight based on the proportion of benefits, that is, the larger the benefit of an agent is, the more influential its preference is. Similarly, agent i interacts with agent j if $|x_i(t) - x_j(t)| \le \varepsilon$ and $i \ne j$. The preference of agent i evolves according to the opinion updating rule, written as

$$x_i(t+1) = \begin{cases} \dfrac{m_i(t)x_i(t)}{b_i(t)} + \sum\limits_{j\in N_i(t)} \dfrac{m_j(t)x_j(t)}{b_i(t)}, & \|N_i(t)\| > 0 \,\&\, b_i(t) > 0 \\ x_i(t), & \text{Others} \end{cases}. \tag{2}$$

where $m_i(t)$ denotes the benefit of agent i at time t, and $b_i(t)$ denotes the total benefits of agent i and agents in the set $N_i(t)$, that is, $b_i(t) = m_i(t) + \sum_{j\in N_i(t)} m_j(t)$. When $\|N_i(t)\| = 0$ or $b_i(t) = 0$ agent i still sticks to its preference at time $t+1$. As time passes, preferences in multi-agent systems change from disorder to order and form several preference clusters, namely, subpopulations, or reach the state of preference consensus. Enterprises in the same subpopulation have the same preference.

3.2 Evolutionary game of pollutant abatement

Some enterprises emit pollution in the production process. To protect the environment in the region in charge, regulators supervise the behavior of enterprises' pollutant abatement. Enterprises select the pollutant abatement strategy (strategy C) or non-abatement strategy (strategy D) according to benefit comparison and their preferences.

There are two goals of pollutant abatement. A maximum goal (T') can be obtained if all enterprises adopt strategy C. Regulators set a tolerable minimum goal ($T < T'$) to prevent environmental deterioration. We consider that all enterprises have a homogeneous scale of production. Thus, the goal of each enterprise is T'/N.

The parameter e represents the total amount of pollutant abatement in the region. Regulators adopt different punishment methods according to the effect of pollutant abatement. Regulators shut down supervised enterprises adopting strategy D if $e < T$. Otherwise, regulators only fine supervised enterprises adopting strategy D.

In the initial state, each enterprise selects strategy C or D with equal probability. W, q, and c denote initial endowment, pollutant emission without abatement, and the unit pollutant abatement cost. Besides, regulators collect taxes, and the tax rate of unit pollutant is μ. Considering the limited supervision ability, we introduce $p' \in [0,1]$ to denote the supervision ability: regulators supervise $p'N$ enterprises. If an enterprise is shut down, the benefit is 0. If an enterprise is fined, the amount of the fine is f.

Based on the above assumptions, the benefit of each enterprise that is shut down is 0. the benefit of each enterprise that is fined is $W - \mu q - f$. The benefit of each enterprise selecting strategy D without being supervised is $W - \mu q$. The benefit of each enterprise selecting strategy C is $W - cT/N - \mu(q - T/N)$. The evolutionary game process of pollutant abatement of regional enterprises under supervision is shown in Figure 1.

In previous studies, the Fermi rule is a common strategy updating rule. This paper proposes a modified Fermi rule combining the classic Fermi rule and the enterprise's preference, as shown in Eq. 3.

$$P_{S_i\to S_j}(t) = \begin{cases} \dfrac{1}{1+\exp\left[\left(\mathrm{m}_i(t)\text{-}\mathrm{m}_j(t)\right)/\kappa\right]} + x_i(t) & \text{if } x_i(t) < 0 \text{ and } S_j = D \\ \dfrac{1}{1+\exp\left[\left(\mathrm{m}_i(t)\text{-}\mathrm{m}_j(t)\right)/\kappa\right]} - \mathrm{x}_i(t) & \text{if } x_i(t) > 0 \text{ and } S_j = C \\ \dfrac{1}{1+\exp\left[\left(m_i(t)\text{-}\mathrm{m}_j(t)\right)/\kappa\right]} & \text{Others} \end{cases}. \tag{3}$$

where $P_{S_i\to S_j}$ denotes the probability that enterprise i follows the strategy of enterprise j at time $t+1$. S_i refers to the current strategy of enterprise i. Based on the strategy updating rule, enterprise i randomly chooses an enterprise in the set of $N_i(t)$. As seen in Eq. 3, RA enterprises prefer adopting strategy C, whil RS enterprises prefer adopting strategy D. The parameter of κ represents the decision noise, and usually $\kappa = 0.1$.

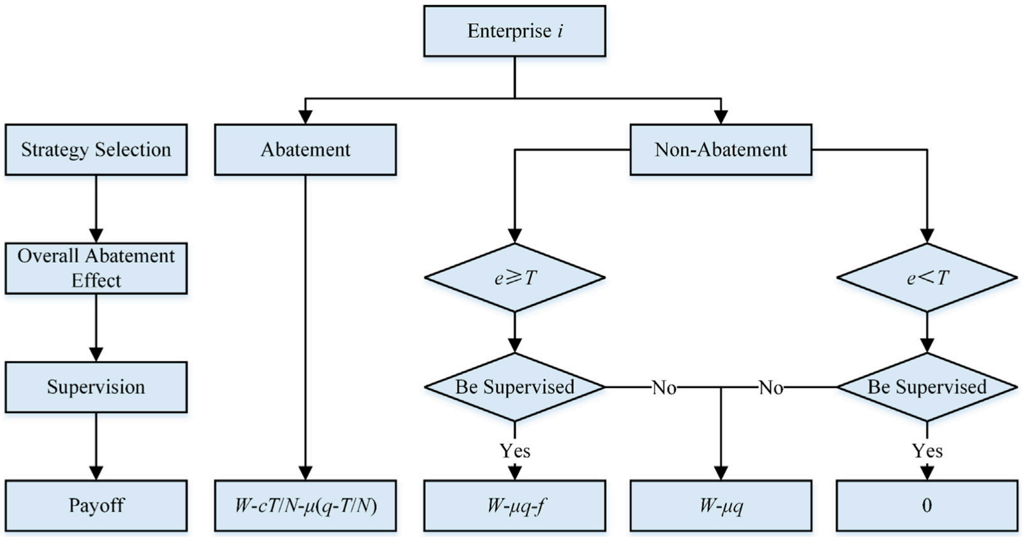

FIGURE 1
The game process of pollutant abatement of regional enterprises.

3.3 Supervision mechanism

There are two supervision mechanisms: general supervision (GS) and smart supervision (SS). In previous studies (Alpízar et al., 2004; Camacho-Cuena and Requate, 2012; Fan et al., 2017), regulators could only randomly choose a part of enterprises to supervise without considering preferences, which is named GS mechanism in this paper.

In the SS mechanism, regulators cannot distinguish the enterprises' preferences in the initial state. Regulators establish a file for each enterprise, which is described as a vector $\lambda_i = (\lambda_{i1}, \lambda_{i2}, \cdots \lambda_{ir} \cdots)$. λ_i refers to the supervision file of enterprise i, and λ_{ir} is the rth supervision result of enterprise i. If enterprise i adopts strategy C under supervision, $\lambda_{ir} = 1$. Otherwise, $\lambda_{ir} = 0$. If enterprise i is not supervised, λ_i does not change at that time.

The parameter of m is the observation period. If the last m supervision results in the λ_i are all 1, regulators identify enterprise i as a RA agent and add enterprise i into the whitelist. In addition, enterprises have no idea about the whitelist.

$y(t)$ refers to the set of members in the whitelist at time t, and $y'(t)$ denotes the set of real RA agents in the whitelist at time t. Since the judgment of regulators might be wrong, we introduce the parameter $p_{y(t)} = \|y'(t)\|/\|y(t)\|$ to measure judgment accuracy, where $\|y(t)\|$ and $\|y'(t)\|$ are the members' numbers of $y(t)$ and $y'(t)$ respectively. At next time, regulators do not supervise the enterprises in the whitelist and choose $p'N$ enterprises in the rest of $N - \|\mathrm{y}(\mathrm{t})\|$ enterprises to supervise.

The whitelist evolves dynamically: 1) At each time, regulators add enterprises that newly meet the condition to the whitelist. 2) The whitelist capability, namely, the maximum number of enterprises in the whitelist, is k. Besides, $\|\mathrm{y}(\mathrm{t})\| \leq k \leq (N - p'N)$. 3) If $\|\mathrm{y}(\mathrm{t})\| > k$ after adding enterprises to the whitelist, regulators should remove the $\| \, \|\mathrm{y}(\mathrm{t})\| - k$ enterprises who have stayed the longest time in the whitelist and keep $\|\mathrm{y}(\mathrm{t})\| = k$. The process of the SS mechanism is shown in Figure 2.

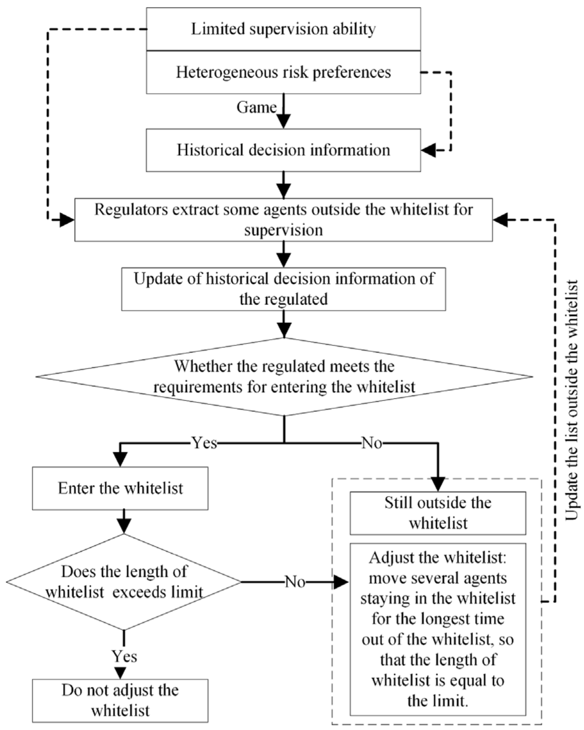

FIGURE 2
The process of the smart supervision mechanism.

4 Numerical simulation and results

4.1 Initialization settings

According to previous studies of opinion dynamics, we first consider a population with homogeneous bounded confidence ε.

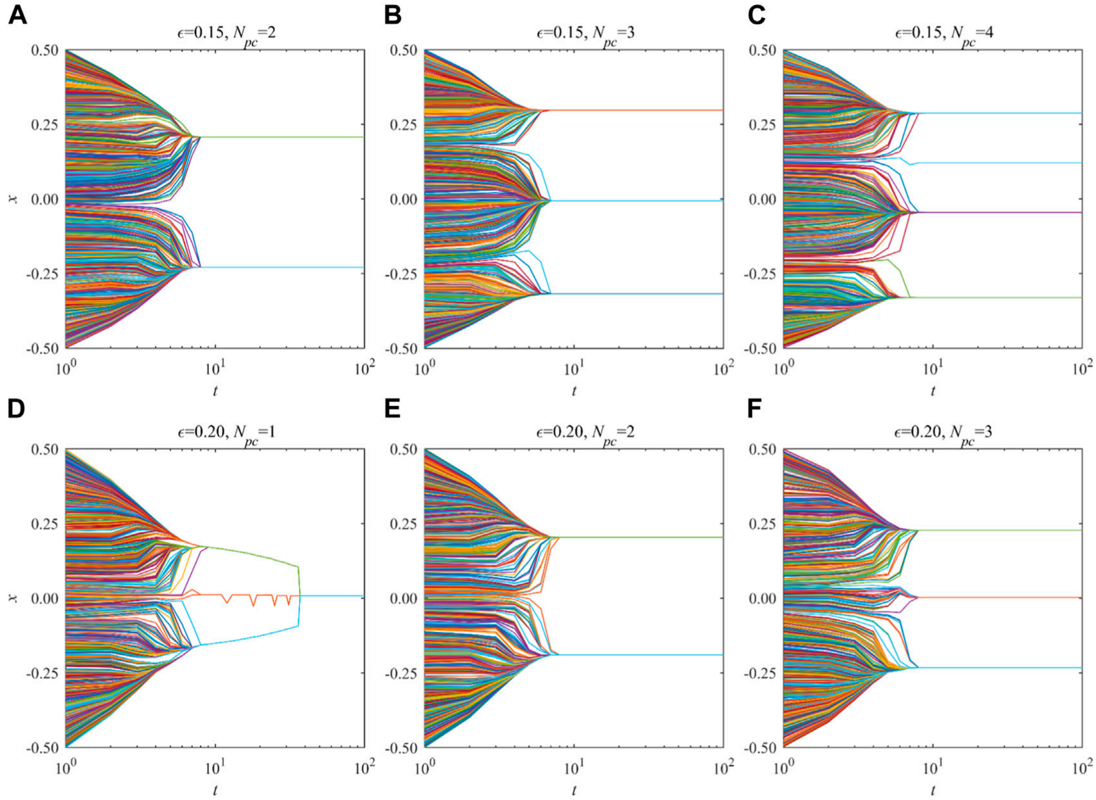

FIGURE 3
Path of preference evolution when ε = 0.15 and 0.20. Each line represents the evolutionary path of an enterprise' preferences. In the initial stage, the enterprise's preferences obey a uniform distribution. Over time, several subpopulations with the same preference are formed in the population. **(A)** $\varepsilon = 0.15$, $N_{pc} = 2$, **(B)** $\varepsilon = 0.15$, $N_{pc} = 3$, **(C)** $\varepsilon = 0.15$, $N_{pc} = 4$, **(D)** $\varepsilon = 0.20$, $N_{pc} = 1$, **(E)** $\varepsilon = 0.20$, $N_{pc} = 2$, **(F)** $\varepsilon = 0.20$, $N_{pc} = 3$.

Apparently, a larger ε leads to a smaller amount of preference clusters (N_{pc}). According to opinion dynamics, the results of opinion evolution are primarily characterized by opinion dispersion, opinion convergence, and opinion consensus. Based on this, we select several states as the research scenarios: (1) $N_{pc} = 2$, (2) $N_{pc} = 3$. Let $\varepsilon = 0.15$, 0.20 respectively, and the results of preference evolution are shown in Figure 3.

In Figure 3, each line represents the preference evolution path of an enterprise: (1) in Figure 3A–C, $N_{pc} = 2$, 3 and 4 when $\varepsilon = 0.15$, (2) in Figure 3D–F, $N_{pc} = 1$, 2, and 3 when $\varepsilon = 0.20$. We find that Figures 3B, E are obtained in most cases. Thus, we select the following scenarios to study the impact of supervision mechanisms on the behavior of pollutant abatement: (1) $N_{pc} = 3$, $\varepsilon = 0.15$, (2) $N_{pc} = 2$, $\varepsilon = 0.20$.

The relevant parameters are set as follows: we set the total number of nodes in the complete graph as $N = 1000$; the minimum goal of pollutant abatement as $T = 2000$; the higher goal of pollutant abatement as $T' = 3000$; the probability that an enterprise chooses strategy C in the initial state as $p = 0.5$; the initial endowment as $W = 10$; the pollutant emission without abatement as $q = 10$; the unit pollutant abatement cost as $c = 0.5$; the tax rate of unit pollutant as $\mu = 0.4$; the penalty amount as $f = 0.4$; the inspection period as $m = 10$. Besides, the above parameters are not changed in the numerical simulation.

The evolution time is set to 2000 to stabilize the results. The values of supervision ability and whitelist capability are set in the range of $p' \in [0, 1]$ and $k \in [0, (1 - p')N]$ respectively. Notably, $k = 0$ means that there is no whitelist, that is, the simulation of $k = 0$ is the result under the GS mechanism. Run 50 times under the same values of parameters to stabilize the results. The final result is determined by averaging the results of 50 times.

In the first scenario, when $N_{pc} = 3$ and $\varepsilon = 0.15$, we can see there are three subpopulations, and the preference values are approximately 0.27, 0.00, and −0.27, respectively, upon reaching a stable state. Three subpopulations, including RS, RN, and RA, are generated. Similarly, in the second scenario, when $N_{pc} = 2$ and $\varepsilon = 0.20$, there are two subpopulations, including a RA subpopulation and a RS subpopulation, where the preference values are approximately 0.19 and −0.19, respectively. Moreover, the number of members in each subpopulation is similar. For example, in the first scenario, the number of members in each subpopulation is basically 333.

4.2 Effect of pollutant abatement

Figure 4 shows the results of the trend of pollutant abatement with p' and k in the cases of GS and SS mechanisms. From an overall perspective, all enterprises select strategy D due to a low supervision ability if $p' \leq 0.4$. In Figure 4A, B, it is clear that a higher supervision ability can enhance the effect of pollutant abatement under both GS and SS mechanisms. Thus, supervision is a necessary condition to

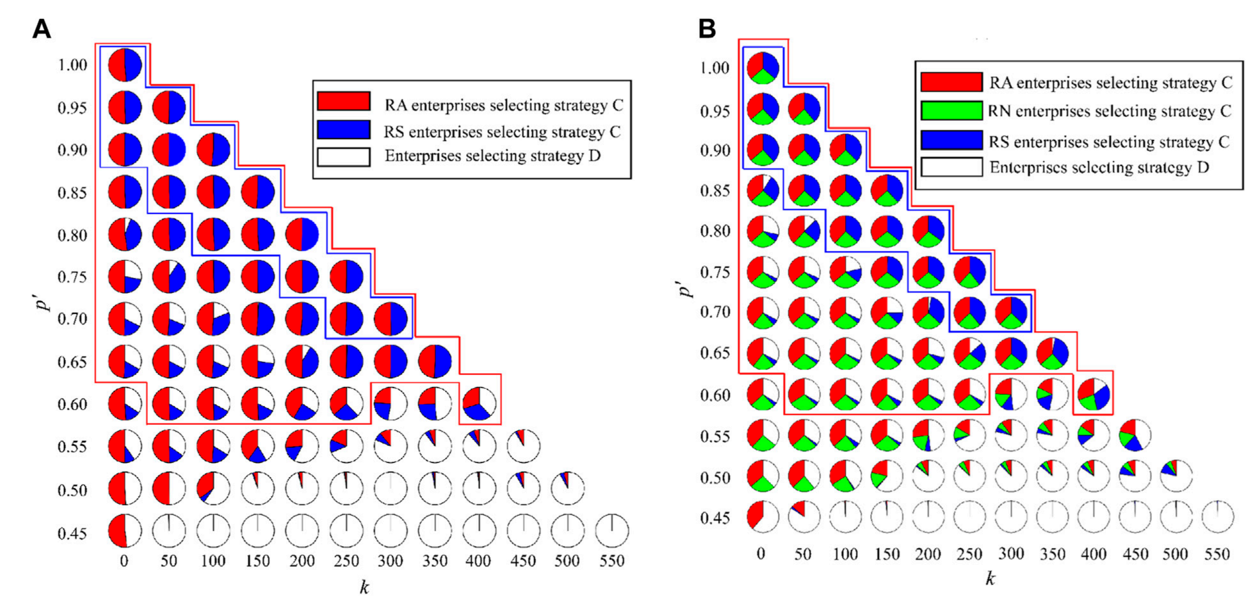

FIGURE 4
Pollutant abatement effect for different p' and k. **(A)** $\varepsilon = 0.20$, **(B)** $\varepsilon = 0.15$. The conditions in the red line are the results achieving the minimum goal of T. The conditions in the blue line are the results achieving the maximum goal of T'.

promote pollutant abatement. Moreover, the result of the SS mechanism is influenced by both supervision ability and whitelist capability. When $p' = 0.45$ and 0.50, the overall effect of pollutant abatement decreases with the increase of whitelist capability. When $p' = 0.55$ and 0.60, the overall effect increases first and then decreases with the increase of k. When $p' \geq 0.65$, increasing the value of k can enhance the overall effect of pollutant abatement.

In the scenario of $\varepsilon = 0.20$, $p' \geq 0.65$ can satisfy the minimum goal of pollutant abatement under the GS mechanism, while $p' \geq 0.60$ can achieve the minimum goal in most cases under the SS mechanism. Considering the maximum goal, regulators need a high supervision ability ($p' \geq 0.90$) to achieve the goal under the GS mechanism, while $p' \geq 0.70$ and $k \geq 250$ can reach that goal. In the scenario of $\varepsilon = 0.15$, shown in Figures 4A, B similar result can be obtained. Thus, compared with the GS mechanism, the SS mechanism can promote achieving the abatement goal with a lower supervision ability.

From the perspective of the subpopulations, in the scenario of $\varepsilon = 0.20$, the conditions for the emergence of cooperative behavior in the RA and RS subpopulations are $p' > 0.45$ and $p' > 0.55$ under the GS mechanism, respectively. However, under the SS mechanism, some RS enterprises select strategy C when $p' < 0.55$. For example, when $p' < 0.50$ and $k = 100$, regulators can supervise enterprises outside the whitelist, where most enterprises are RS agents. Thus, some RS enterprises adopt strategy C. However, enterprises in the whitelist cannot be supervised, which causes a decline in the overall abatement effect. If $p' \geq 0.65$, the supervision ability is high enough. At this time, regulators maintain balanced supervision of different subpopulations. Thus, it can further improve the overall effect of the cooperation level by increasing the whitelist capability.

Similarly, in the scenario of $\varepsilon = 0.15$, under the GS mechanism, abatement behavior appears in the RA subpopulation first ($p' \geq 0.45$), then in the RN subpopulation ($p' \geq 0.50$), and finally in the RS subpopulation ($p' \geq 0.60$). Meanwhile, under the SS mechanism, with a lower supervision ability ($p' = 0.50 - 0.60$), the behavior of pollutant abatement in the RS subpopulation emerges with the increase of k, while the proportion of the abatement behavior in other subpopulations decreases. However, with a higher supervision ability ($p' \geq 0.65$), the proportion of the pollutant abatement behavior in the RA and RN subpopulations does not decrease with the increase of k, which promotes the overall abatement effect.

4.3 Effect of enterprises' benefits

As can be seen in Figure 5A, when $p' = 0.50$, the benefit of the RS subpopulation has an upwards trend with the increase of the whitelist capability, especially in the case of $k = 550$. However, due to the decrease in abatement behavior, the benefits of RA and RN subpopulations are weakened with the increase of k, which also causes the overall abatement effect to decrease. In Figure 5B if $p' = 0.60$ and $0 \leq k \leq 250$, the overall benefit increases with the increase of k due to the stable abatement behavior in the RA and RN subpopulations and the abatement improvement in the RS subpopulation. However, when $k > 250$, regulators strengthen supervision of the RS subpopulation and neglect other subpopulations, which causes the proportion of enterprises selecting strategy D increases. Thus, the number of punished enterprises increases in the RA and RN subpopulations, and the overall benefits trend downward. In Figure 5C, with a higher supervision ability, the benefits of the RS subpopulation and overall population increase with the increase of k due to the promotion of abatement behavior.

Moreover, the benefits of subpopulations with the same abatement proportion may differ according to supervision

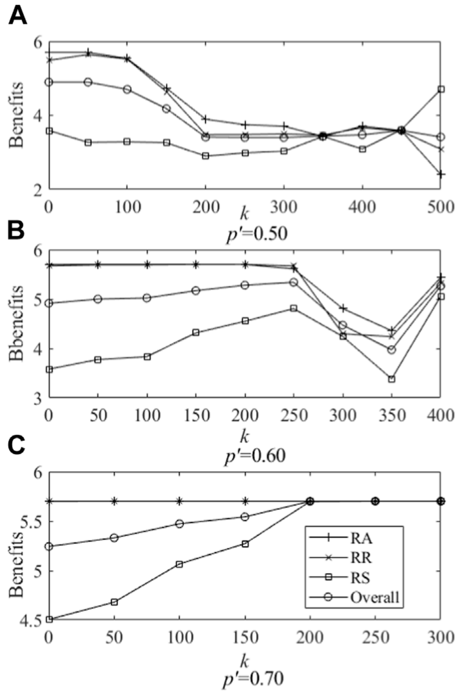

FIGURE 5
Average benefit of each subpopulation (ε = 0.15). **(A)** p' = 0.50, **(B)** p' = 0.60, **(C)** p' = 0.70.

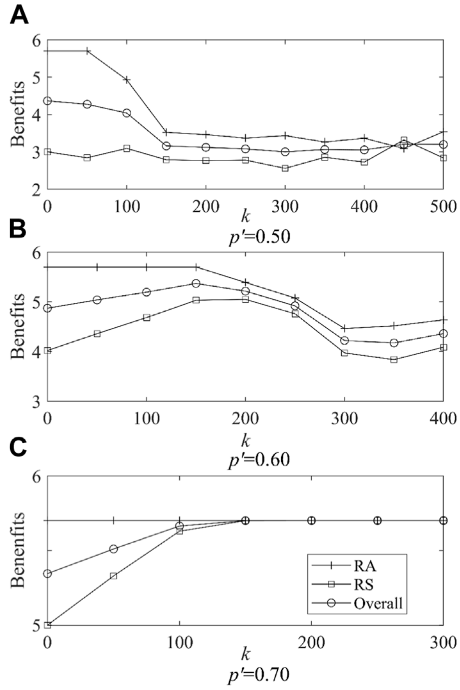

FIGURE 6
Average benefit of each subpopulation (ε = 0.20). **(A)** p' = 0.50, **(B)** p' = 0.60, **(C)** p' = 0.70.

mechanisms. For example, in Figure 4B, we can see that pollutant abatement effects of three subpopulations (RA, RN, and RS) are similar if p' = 0.60 and k = 350. The abatement proportions of three subpopulations (RA, RN, and RS) are 0.4805, 0.4590, and 0.4640. However, in the above case, the benefits of the three subpopulations are 4.3593, 4.2401, and 3.3887, respectively, as shown in Figure 5B. Regulators pay more attention to RS enterprises under the SS mechanism, so RS enterprises are punished more at the same cooperation level. Thus, the benefit of the RS subpopulation is the least. The results prove that regulators can accurately supervise the RS subpopulation.

In Figure 6, the benefit trend with the change of p' and k when ε = 0.20 is similar to the one when ε = 0.15. In a lower supervision ability, the overall benefit decreases with the increase of k, while the overall benefit increases with a higher supervision ability. Besides, the difference between the subpopulation benefits is noticeable. In most cases, the benefit of the RA subpopulation is higher, which is caused by two reasons: 1) a higher cooperation level in the RA subpopulation, and 2) regulators pay more attention to the RS enterprises.

4.4 Effect of judgment accuracy

Regulators need to judge the enterprise's preference according to the previous abatement behavior. However, regulators may mistakenly identify RS enterprises as RA ones and add them to the whitelist. We analyse the judgment accuracy of the whitelist member's preference in different cases based on the simulation result.

In Figure 7, we depict the judgment accuracy in the scenarios of ε = 0.15 and 0.20 respectively. On the one hand, if the whitelist capability remains unchanged, the judgment accuracy decreases as the supervision ability increases. The reason is that the abatement effect is improved with the rise of the supervision ability. Thus, all enterprises' behaviors are similar under a higher supervision ability, which makes it difficult for regulators to find real RA enterprises. On the other hand, if the supervision ability remains unchanged, the judgment accuracy decreases with the increase of whitelist capability. Due to the relatively fixed number of RA enterprises, some RS or RN enterprises are added to the whitelist with the rise of k, which leads to a decrease in judgment accuracy. However, if the supervision ability is higher, the decline of the judgment accuracy with the increase of k does not affect the abatement effect. Similar behaviors among different subpopulations lead to a lower judgment accuracy. Moreover, if all enterprises adopt the same strategy, the judgment accuracy is close to 0.5.

Compared Figure 7A with 7(b), we can see some differences between different ε. Set other parameters the same, judgment accuracy of ε = 0.20 is higher than that of ε = 0.15. For example, when p' = 0.65 and k = 150, the values of judgment accuracy in Figures 7A, B are 0.8120 and 0.9598, respectively. The reason is that there are RN enterprises when ε = 0.15 and the preference difference between RN subpopulation and RA subpopulation is smaller than that of the RS subpopulation. Thus, it is harder for regulators to find out true RA enterprises.

4.5 Effect of the observation period

As shown in Figure 4, the introduction of the SS mechanism leads to the decline of the cooperation rate if p' = 0.50. Therefore, the SS mechanism may not constantly improve the level of

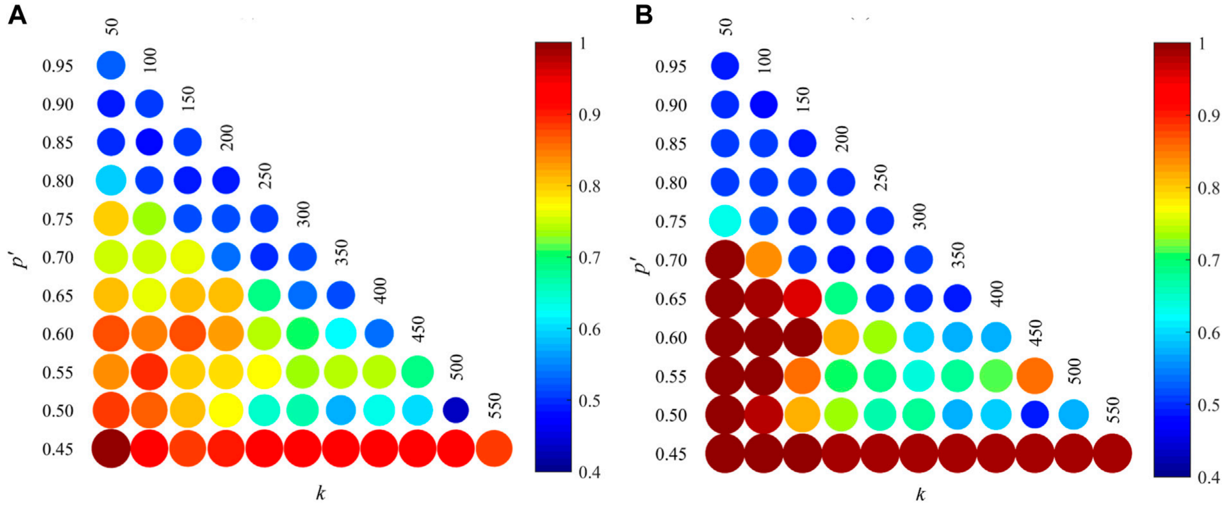

FIGURE 7
Judgment accuracy for different p' and k. **(A)** $\varepsilon = 0.15$, **(B)** $\varepsilon = 0.20$.

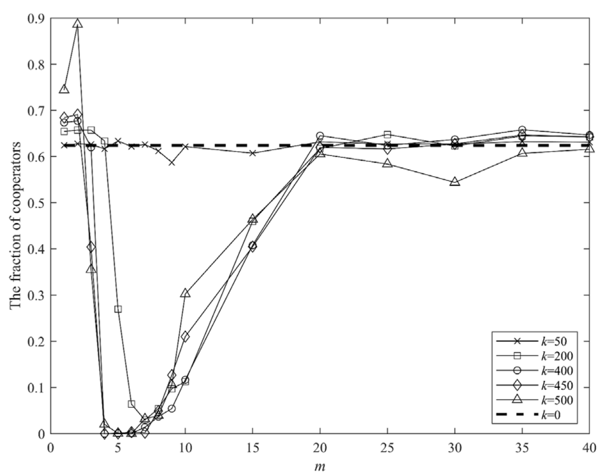

FIGURE 8
The fractions of cooperators for different m and k.

cooperation, especially in the case of a lower supervision ability. To achieve a better effect of pollutant abatement, the observation period in the SS mechanism is tested.

Figure 8 shows the effect of observation period on the fraction of cooperators. In Figure 8, the change of m has no significant effect on the cooperation rate if $k = 50$. Besides, the cooperation rate in the case of $k = 50$ is similar to the one under the GS mechanism. Second, the cooperation rate first decreases and then increases with increasing m in the cases of $k = 200$, 400, 450, and 500, and finally remains a steady cooperation rate. Finally steady cooperation rate is not significantly different from the one under the GS mechanism. Third, a higher cooperation level can be achieved if the observation period is short and the whitelist capability is large. For example, if $m = 2$ and $k = 200$, the cooperation rate is 0.886, higher than the one under the GS mechanism. Fourth, with the increase in the observation period, the number of enterprises that meet the conditions for entering the whitelist decreases, and the dynamic adjustment of the whitelist weakens. Some enterprises stay on the whitelist for a long time due to the slow dynamic adjustment, which leads to the fluke of adopting the defection strategy. Finally, with the further increase of the observation period, especially if $m \geq 20$, the number of enterprises who can enter the whitelist decreases and even becomes 0 due to the strict restrictions. At that time, the whitelist is invalid, so the cooperation rates under the SS and GS mechanisms are similar.

Thus, facing the issue of reducing the cooperation rate caused by the SS mechanism, a higher cooperation level can be achieved by appropriately shortening the observation period and increasing the whitelist capability.

5 Conclusion and implications

It is evident that supervision can improve the pollutant abatement effect. To optimize supervision efficiency, we discuss how regulators supervise enterprises under the collective risk of pollutant abatement considering heterogeneous preferences and limited supervision ability. First, a coevolution model for game and preference is proposed based on the theories of the evolutionary game and opinion dynamics. Second, by introducing the concepts of the whitelist and observation period, we propose a smart supervision mechanism considering enterprises' preferences. Besides, we prove that the smart supervision mechanism can promote pollutant abatement more than the random supervision through the simulation. Furthermore, some recommendations are put forward to improve regulators' supervision efficiency.

The results show that (1) the effect on pollutant abatement under the smart supervision mechanism is better than that under the random supervision mechanism. Although the smart supervision mechanism leads to the decline of cooperation rate in a few cases compared with the random supervision mechanism, shortening the observation period and increasing the whitelist capability can improve the effect of pollutant abatement. Thus, regulators can achieve the abatement goal with a lower supervision ability in the smart supervision mechanism. (2) Generally, a higher benefit can be achieved if the pollutant abatement is better. However, regulators pay more attention to the risk-seeking enterprises under the smart supervision mechanism, so the risk-seeking ones are punished more. It causes the risk-seeking enterprises have a lower benefit at the same cooperation level compared with other enterprises. (3) Regulators can accurately judge the enterprises' preferences according to historical decision differences. The judgment accuracy declines if there are risk-neutral enterprises in the population or minor decision differences.

Based on the research conclusions, we put forward the following suggestions. (1) Under the limited supervision ability, regulators should consider enterprises' differences. Risk preferences can affect the decision behavior and cause enterprises to implement pollutant abatement with different probabilities under the same situation. Thus, regulators should adopt a more targeted supervision mechanism. (2) Regulators can use historical decision-making to judge enterprises' preference type. Moreover, regulators can strengthen the supervision of enterprises that adopt the strategy of non-abatement more. In this way, regulators can make the limited supervision ability more efficient. (3) Combined with the supervision ability, setting appropriate whitelist capacity and observation period can achieve a better supervision effect. If the supervision is higher, a larger whitelist capability can improve the cooperation level. Notably, if the supervision ability is lower, shortening the observation can achieve a better effect.

Considering practical applications, a similar supervision mechanism has been implemented in 2023. In Xingtai City, Hebei Province, China, the Market Supervision Administration conducted a joint random inspection of key emission units from November 6 to 30 November 2023 (Xingtai, 2023). The inspection covered all key emission units (enterprises) in the city, with a sampling rate of 10%. Leveraging the national Internet + regulatory credit information, the Market Supervision Administration employed a differentiated random inspection based on enterprise credit risk. For those with lower credit risk, the inspection rate was reasonably reduced, while for those with higher credit risk, the inspection rate was increased. The Market Supervision Administration categorized enterprise risks into four levels, from low to high: A, B, C, and D. The sampling rate for B-risk was 6%, for C-risk was 13%, and for D-risk was 40%. Whether the supervision mechanism considering the differences in enterprises' preferences can improve the environment in practice still requires long-term observation. However, the regulatory authorities' ability to use differentiated inspections based on credit information marks a progress in management.

Nevertheless, some limitations still exist. We assume enterprises have a preference for selecting strategies in this paper. Besides, the amount of pollutant abatement is unchanged if the enterprise is a cooperator. Namely, we only consider the influence of preferences on strategy selection and neglect the impact on the amount of pollutant abatement. A better understanding of decision preference is needed to enrich further the research on the supervision mechanism of pollutant abatement among regional multi-enterprises. Besides, this study places a greater emphasis on theoretical framework construction and exploration, laying the foundation for empirical research. Future research endeavors may pivot towards empirical data collection and analysis to substantiate and enhance the feasibility and applicability of our theoretical model.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

XW: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Writing–original draft. DZ: Methodology, Software, Supervision, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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