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Evolutionary Game Analysis of AI+ Green Energy Innovation Based on Consumer Preference and Policy Subsidies

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Abstract: The continuous advancement and promotion of green energy products are gradually reducing consumers' dependence on traditional energy sources. Due to the limitations of big data applications and constraints of AI technology diffusion, the adoption of green energy has yet to achieve widespread implementation or full consumer acceptance. Having employed a tripartite game-theoretic approach, this study selected governments, enterprises, and consumers as key players to analyze the evolutionary game strategies in AI-driven green energy innovation. A three-party evolutionary game model was constructed and adopted, in order to reveal critical factors that affect the decisions of these stakeholders on green energy innovation and consumption. The findings indicated a positive correlation between the intensity of consumer preference for green energy products and enterprises' decisions to pursue the related AI-enhanced innovation. Although firms still weigh the impact incurred by the costs of research and development on profitability, the likelihood of enterprises engaging in AI-driven green energy innovation increases significantly alongside the elevating consumer preference for green energy products.

Keywords: Green energy (GE); Consumption guidance; AI+; Big data

1 Introduction

Driven by the intensifying global climate crisis and the "dual-carbon" goals in China, green energy consumption has become central to the country's energy transition. Currently, China's energy mix remains dominated by fossil fuels. To address climate change and ecological pressures, the nation has set strategic targets of achieving carbon peak by 2030 and carbon neutrality by 2060, with green energy consumption being pivotal to realizing these objectives. Concurrently, rapid advances in new energy technologies such as photovoltaic, wind power, and hydrogen energy, have provided technical support for green energy adoption, while growing public environmental awareness has laid a social foundation for green consumption. The rise of green energy industries, including new energy vehicles and renewable-energy equipment manufacturing, has generated new economic growth drivers, spurred the green upgrading of traditional sectors, and created substantial employment opportunities. Green consumption behaviour encourages the public to adopt low-carbon lifestyles, advances the concept of ecological civilization, and optimizes resource allocation through policy instruments such as green-certificate trading and subsidy mechanisms, thereby fostering coordinated environmental and economic development. Furthermore, green energy consumption helps China reduce its reliance on imported fossil fuels and enhances energy security. In the future, green energy consumption will not only be essential for mitigating climate change but also serve as a key engine for high-quality development, thus positioning China favourably in the global green economy.

Government financial support for green energy is a crucial driver of industrial development in the early stage, yet the design of subsidies significantly shapes policy effectiveness. Studies generally indicated that government subsidies exerted a non-linear impact on green energy enterprise innovation, with an optimal range-subsidies that are too low to induce rent-seeking behaviour, while excessively high subsidies can crowd out firms' own research and development (R&D) investments. Recently, most enterprises, especially in the wind-energy sector, have not yet entered this optimal range [1]. In the photovoltaic field, benchmark electricity prices and R&D subsidies have helped expand production capacity, but issues remain regarding the mismatch between subsidy scales and regional resource endowments, reflecting how incomplete policy contracts can create risks of "subsidy gaming" and increase fiscal burdens [2]. In addition, China promotes the implementation of wind and photovoltaic projects through land-use policies, thus effectively boosting installed capacity [3], whereas developed countries rely on comprehensive legal and financial instruments to establish long-term support systems [4]. Future policy directions may include shifting from fixed feed-in tariffs to quota systems and green-certificate trading to alleviate fiscal pressure [5]. Meanwhile, countries in the Global South have shaped distinct development pathways through independent, balanced, or dependent industrial policies, underscoring the importance of strategic policy positioning [6]. However, most existing studies focused on single policy instruments and lacked systematic evaluation of coordinated policy mechanisms, such as subsidies, land use, quotas, and green certificates, while paying insufficient attention to subsidy equity amid regional disparities.

Consumer preferences play a decisive role in green-product marketing, and their heterogeneity and psychological traits directly influence the outcomes of policy design. Research revealed a non-linear relationship between the level of consumer anxiety and the effectiveness of subsidy-policy: subsidies should be increased when anxiety is either low or high, but reduced when it is moderate [7]. In the new-energy vehicle sector, the effectiveness of price discounts and green-tax policies in the "post-subsidy era" depends on consumer preferences and product greenness; green taxes prove more effective when consumers prefer conventional fuel vehicles [8]. Subsidies for charging service fees are more impactful than those for charging infrastructure construction, with the optimal subsidy ratio first decreasing and then increasing as range anxiety rises [9]. Consumers' perceived quality of policy in terms of affordability and stability affects purchase intention through the mediating role of trust, with notable urban-rural differences [10]. Moreover, against the backdrop of declining subsidies, unrestricted driving privileges and easier license-plate access have become the most influential policy factors affecting vehicle purchases [11]. Nevertheless, most existing studies concentrated on single products or policy tools and lacked integrated analyses of multi-category green consumption behaviours. These works seldom examined the dynamic evolution of consumer preferences and the adaptability of policies in the long run.

AI technology is emerging as a key enabler of green innovation and sustainable development, with applications extending from manufacturing enterprises to diverse fields, such as consumer behaviour and energy investment. Studies demonstrated that AI adoption positively influenced green innovation in manufacturing firms, with structural and relational capital significantly promoting such innovation and the positive moderating role of AI [12]. AI is being widely deployed across industries, to guide corporate green innovation and steer manufacturing toward sustainable development [13]. AI technology can also facilitate the cultivation of green and low-carbon consumption values among university students, in order to promote resource conservation and environmental protection [14]. In the context of global climate change, technological progress offers hope for mitigation; the UN Climate Change Conference (COP29) highlighted scientific and technological innovation as a driver of green and sustainable development [15]. On the consumer side, the impact of AI recommendations on the purchase intention of green products varies: AI-agent recommendations are generally weaker than human-agent recommendations, though this difference diminishes when AI is highly anthropomorphized [16]. The integration of AI algorithms with quantitative investment methods promotes the development of new-energy industry investments, with the XGBoost model outperforming others [17]. The new-energy industry in Xinjiang is exploring an "AI+ energy" pathway, utilizing 5G and other technologies to enhance innovation capacity [18]. Yet, most existing research focused on the effects of applying AI technology and lacked systematic analysis of the synergistic mechanisms between AI and green innovation, while rarely addressing ethical risks and social equity in AI deployment.

Existing literature has systematically revealed the driving effects of policy, technology, economy, and international cooperation on green-energy development, thus laying a foundation for understanding its complexity. However, with the rapid penetration of AI technology, the integration of big data and AI demonstrates key potential in guiding green energy consumption, an area requiring further exploration. Current research lacks empirical analysis of the synergy between AI and big data about energy, particularly overlooking systematic investigation into the dynamic and interactive mechanism of "consumer preferences-government subsidies-enterprise AI-enabled green-energy innovation". This study examined how big data about energy fused with AI technology can guide consumption preferences through a game-theoretic model. It aims to provide a theoretical basis for the government to design precise subsidy policies and for enterprises to optimize decisions on innovation, thereby constructing an accurate, coordinated, and sustainable green-innovation support system that could effectively advance the achievement of the "dual-carbon" goals.

2 Relevant Assumptions and Parameters

First, drawing on the Theory of Planned Behaviour [19] and the Consumer Green Behaviour Model [20], this study posits that, compared with deliberative decision-making, consumers' intuitive or heuristic decision-making enhances their willingness to sustain green behaviours. Accordingly, x is defined as the probability of preferring green energy consumption, with a value range of (0,1). This probability is influenced by the environmental awareness, social norms, and intuitive thinking of consumers.

Second, based on research on China's policy diffusion models and mechanisms [21], which highlights the multi-directional yet predominantly top-down hierarchical nature of policy diffusion, y is defined as the probability that the government implements green energy consumption subsidies. This probability is shaped by fiscal conditions, the urgency of environmental targets, and political pressures.

Third, grounded in Western theories of public policy innovation diffusion [22], which identify learning, imitation, socialization, competition, and coercion as key diffusion mechanisms, enterprises are assumed to balance policy signals and efficiency gains in market competition. Hence, z is defined as the probability that an enterprise adopts AI-enabled optimization of green energy supply, which is affected by factors such as technological comparative advantage, compatibility, complexity, and observability.

To focus on the strategic interactions within the game, the model is simplified by treating x, y, and z as linear functions of their respective influencing factors.

Finally, integrating insights from welfare economics [23] and behavioural economics [24], the study recognized that enterprises could enhance efficiency by aligning social responsibility with consumer expectations. In this connection, three benefit variables were introduced: F denotes the utility of consumer social identity, G represents the environmental benefits for the government, and H signifies the reputational benefits for enterprises. Specific assumptions are detailed as follows:

Hypothesis 1: Strategy Selection Probability

Green Energy Consumption Preference Probability (x): The likelihood that consumers opt for green products, defined as $(0 < x < 1)$.

Government Subsidy Probability (y): The probability that the government provides subsidies for green energy consumption, defined as $(0 < y < 1)$.

AI-Enabled Green Energy Optimization Probability (z): The probability that firms choose to optimize green energy supply through big-data-integrated AI, defined as $(0 < z < 1)$.

Hypothesis 2: Tax Rate Parameters of Green Energy Policy

Government Tax Rate (T): The standard tax rate imposed by the government on corporate earnings.

Green Energy Preferential Tax Rate (U): The reduced tax rate granted by the government to enterprises that adopt green energy technologies.

Hypothesis 3: Price and Cost Parameters

Traditional Energy Price (P_1): The price at which enterprises supply conventional energy.

AI-Enhanced Green Energy Price (P_2): The price of green energy optimized through big-data-integrated AI.

Green Energy Price (P_3): The price at which enterprises supply green energy without AI enhancement.

Big-Data-Integrated AI R&D Cost (C): The investment made by green-energy enterprises in developing big-data-fused AI technologies.

Green Energy Consumption Subsidy (R_1): Government subsidy provided to consumers of green energy.

Green Energy Production Subsidy (R_2): Government subsidy directed toward green-energy producers.

It is assumed that the Green Energy Price P_3 exceeds the AI-Enhanced Green Energy Price P_2, which in turn is higher than the Traditional Energy Price P_1. When enterprises supply AI-enhanced green energy, consumers will give priority to purchasing it. Besides, it is assumed that the traditional energy consumption subsidy R_3 is lower than the green energy consumption subsidy R_1.

Hypothesis 4: Social Benefit Parameters

Honor-Based Consumer Utility (F): The social identity benefits derived from consuming green energy.

Government Environmental Benefit (G): The environmental gains achieved by the government through the presence of enterprises responsible for local green energy supply or consumption in the market.

Corporate Reputational Benefit (H): The brand premium obtained by enterprises as a result of big-data-integrated AI innovation.

3 Construction and Solution Analysis of the Tripartite Game Model

The construction of tripartite benefit matrix is as shown in Table 1.

3.1 Solution Analysis

(1) Analysis of Expected Return from Consumers

Suppose E_{x1} is the expected return during the period when consumers prefer green energy:

$$E_{x1} = yR_1 + z\left(F - P_2 + P_3\right) - P_3 \tag{1}$$

Suppose E_{x2} is the expected return when consumers prefer traditional energy:

$$E_{x2} = yR_3 - P_1 \tag{2}$$

Suppose E_x is the average expected return of consumers:

$$E_x = xE_{x1} + (1-x)E_{x2} \tag{3}$$

(2) Analysis of Government Expected Revenue
Suppose E_{y1} is the expected return during the period of government subsidies:

$$E_{y1} = G(x+z-xz) - xR_1 - zR_2 + xzP_2t(1-u) + (P_1t - R_3)(1-x) \tag{4}$$

Suppose E_{y2} is the expected return during the period when the government does not subsidize:

$$E_{y2} = G(x+z-xz) + xzP_2t(1-u) + P_1t(1-x) \tag{5}$$

Suppose E_y is the average expected return of the government:

$$E_y = yE_{y1} + (1-y)E_{y2} \tag{6}$$

(3) Analysis of Expected Return of Enterprises
Suppose E_{z1} is the expected return during the "AI+ Green Energy" innovation period of the enterprise:

$$E_{z1} = P_1(1-t) - C + H + x(P_2 - P_1) + y(R_2 - P_1t) - xyR_2 \tag{7}$$

Suppose E_{z2} is the expected return during the "AI+ Green Energy" innovation period of the enterprise:

$$E_{z2} = (|\ 1-x\ |)(P_1 - P_1t) \tag{8}$$

Suppose E_z is the average expected return of the government:

$$E_z = zE_{z1} + (1-z)E_{z2} \tag{9}$$

Table 1. Three-party benefit matrix of governments, enterprises, and consumers

Combination of Strategies			Consumer Benefits	Government Revenue	Corporate Income
Consumer preference for green energy (x)	Government subsidies (y)	AI+green energy innovation (z)	R_1+F-P_2	$G-R_1-R_2$ $+P_2t(1-u)$	$P_2-P_2t(1-u)$ $-C+R_2+H$
		Green energy does not innovate $(1-z)$	R_1-P_3	$G-R_1$	0
	Government does not subsidize $(1-y)$	AI + green energy innovation (z)	$F-P_2$	$G+P_2t(1-u)$	$P_2-P_2t(1-u)$ $-C+H$
		Green energy does not innovate $(1-z)$	$-P_3$	G	0
Consumer preference for green energy $(1-x)$	Government subsidies (y)	AI+ green energy innovation (z)	R_3-P_1	P_1t-R_2 $-R_3+G$	P_1-P_1t $-C+H+R_2$
		Green energy does not innovate $(1-z)$	R_3-P_1	P_1t-R_3	P_1-P_1t
	Government does not subsidize $(1-y)$	AI+ green energy innovation (z)	$-P_1$	$P_{1t}t+G$	P_1-P_1t $-C+H$
		Green energy does not innovate $(1-z)$	$-P_1$	P_1t	P_1-P_{1t}

3.2 Dynamic Equation Analysis of Tripartite

Replication: From the expressions above, the replication dynamic equations of consumers, governments, and enterprises are F_x, F_y, and F_z respectively:

$$F_x = x(1-x)\left[z(F - P_2 + P_3) + y(R_1 - R_3) - P_3 + P_1\right] \tag{10}$$

$$F_y = y(1-y)\left[-xR_1 - zR_2 - R_3(1-x)\right] \tag{11}$$

$$F_z = z(1-z)\left[-C + H + x\left(P_2 - P_1 t\right) + y\left(R_2 - P_1 t\right) - xyR_2\right] \tag{12}$$

According to the above three-way replication dynamic equation, the Jacobian matrix J can be calculated as follows:

$$J = \begin{pmatrix} J1 & J2 & J3 \end{pmatrix} \tag{13}$$

$$J1 = \begin{pmatrix} (1-2x)\left[z\left(F - P_2 + P_3\right) + y\left(R_1 - R_3\right) - P_3 + P_1\right] \\ y(1-y)\left(R_3 - R_1\right) \\ z(1-z)\left(P_2 - P_1 t - yR_2\right) z(1-z)\left(P_2 - P_1 t - yR_2\right) \end{pmatrix} \tag{14}$$

$$J2 = \begin{pmatrix} x(1-x)\left(R_1 - R_3\right) \\ (1-2y)\left[-xR_1 - zR_2 - R_3(1-x)\right] \\ z(1-z)\left(R_2 - P_1 t - xR_2\right) \end{pmatrix} \tag{15}$$

$$J3 = \begin{pmatrix} x(1-x)\left(F - P_2 + P_3\right) \\ -y(1-y)R_2 \\ (1-2z)\left[-C + W + x\left(P_2 - P_1 t\right) + y\left(R_2 - P_1 t\right) - xyR_2\right] \end{pmatrix} \tag{16}$$

Setting $F_x = F_y = F_z = 0$, the values of x, y, and z are found to be either 0 or 1. The corresponding eigenvalues at different equilibrium points can then be calculated, as shown in Table 2.

Table 2. Characteristic points under different equilibrium values

Equilibrium Points	Eigenvalue λ_1	Eigenvalue λ_2	Eigenvalue λ_3
(0,0,0)	$P_1 - P_3$	$-R_3$	$H - C$
(0,0,1)	$F - P_2 + P_1$	$-R_3 - R_2$	$C - H$
(0,1,0)	$R_1 - R_3 - P_3 + P_1$	R_3	$-\mathrm{C} + \mathrm{H} + \mathrm{R}_2 - \mathrm{P}_1 t$
(0,1,1)	$F - P_2 + P_1 + R_1 - R_3$	$R_3 + R_2$	$\mathrm{C} - \mathrm{H} - \mathrm{R}_2 + \mathrm{P}_1 t$
(1,0,0)	$P_3 - P_1$	$-R_1$	$-\mathrm{C} + \mathrm{H} + \mathrm{P}_2 - \mathrm{P}_1 t$
(1,0,1)	$-F + P_2 - P_1$	$-R_1 - R_2$	$\mathrm{C} - \mathrm{H} - \mathrm{P}_2 + \mathrm{P}_1 t$
(1,1,0)	$-R_1 + R_3 + P_3 - P_1$	R_1	$-C + H + P_2 - 2P_{1t}$
(1,1,1)	$-R_1 + R_3 - P_1 - F + P_2$	$R_1 + R_2$	$\mathrm{C} - \mathrm{H} - \mathrm{P}_2 + 2\mathrm{P}_1 t$

Given that the eigenvalues of an Evolutionarily Stable Strategy (ESS) must be negative, and since R_1, R_2 and R_3 are all greater than 0, the equilibrium points (0,1,0), (0,1,1), (1,1,0), and (1,1,1) are first excluded. Furthermore, according to the earlier assumption that $P_3 > P_1$, the equilibrium point (1,0,0) can also be eliminated. After evaluation, only the points (0,0,0), (0,0,1), and (1,0,1) satisfy the conditions for an ESS equilibrium. These three points are analyzed below.

3.3 Eigenvalue Analysis of Equilibrium Points

Case 1: State (0,0,0)

When $H - C < 0$, consumers exhibit a preference for traditional energy and the government provides no subsidies, so enterprises do not pursue "AI+" innovation. Since traditional energy is priced lower than green energy, consumers favor it on cost-performance grounds. For the government, although subsidies can affect consumer income and behavior, the absence of a revenue-recovery mechanism leads to a "no subsidy" strategy. In this scenario, the incentive for "AI+" innovation depends entirely on the trade-off between social benefits and R&D costs. If the social benefits of innovation cannot offset R&D expenses, enterprises will not undertake "AI+" innovation.

Case 2: State (0,0,1)

When $F - P_2 + P_1 < 0$ and $C - H < 0$, consumers still prefer traditional energy and the government provides no subsidies. Yet, enterprises are willing to pursue "AI+" innovation. If the convenience of using green energy does not outweigh its price premium over traditional energy, consumers will opt for the latter. For enterprises, however, the social benefits from "AI+" innovation exceed R&D costs, and this motivates them to innovate independently.

Case 3: State (1,0,1)

When $-F + P_2 - P_1 < 0$ and $C - H - P_2 + P_1 t < 0$, consumers prefer green energy and the government provides no subsidies. Enterprises continue to promote "AI+" innovation. This state suggests that the additional benefits consumers derive from "AI+ Green Energy" can compensate for the price difference relative to traditional energy. Furthermore, if the R&D costs of "AI+" are lower than the combined value of social benefits plus the green energy price minus the tax-adjusted traditional energy price, enterprises will actively engage in "AI+" innovation.

4 Simulation Analysis and Suggestions of Tripartite Game Model

4.1 Time Variation Analysis

4.1.1 Initial case analysis

As shown in Figure 1, assuming that the probability of consumers preferring green energy (x), the probability of government subsidy provision (y), and the probability of enterprises pursuing "AI+ Green Energy" innovation (z) are all initialized at 0.5, the three evolutionary curves exhibit distinct trajectories.

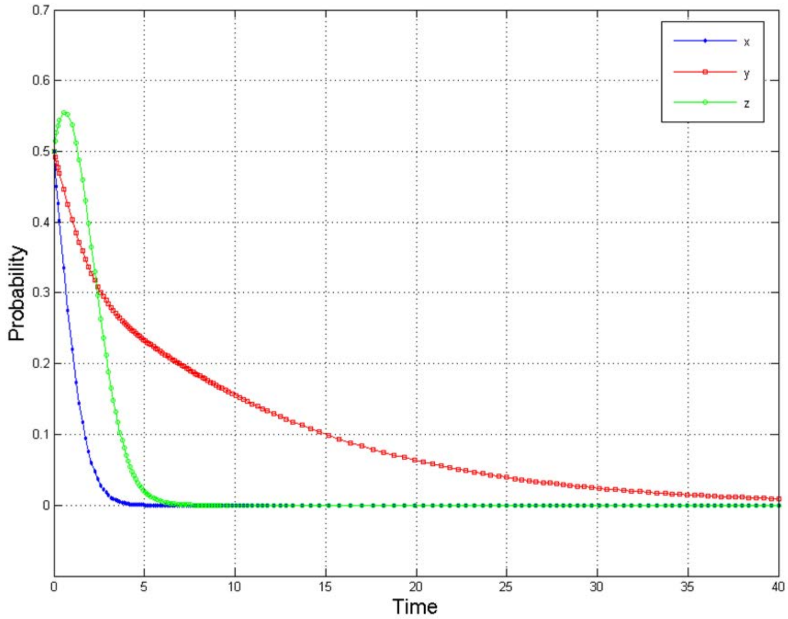

Figure 1. Evolutionary game analysis of initial situation:
$F = 0.2; P_1 = 1; P_2 = 2; P_3 = 3; R_1 = 0.3; R_2 = 0.4; R_3 = 0.1; C = 0.5; H = 0.2; t = 0.1$

First, from the enterprise innovation probability curve Z, the subsidies for green energy production and the social benefits derived from R&D initially motivate enterprises to engage in "AI+ Green Energy" innovation to some extent. However, as the probability of government subsidies decreases, enterprise revenue becomes insufficient to cover R&D costs, and consumers do not anticipate sufficient incremental benefits. As a result, enterprises ultimately revert to a state of no "AI+ Green Energy" innovation.

Second, the consumer preference probability curve X and the government subsidy probability curve Y both exhibit a declining trend, converging toward zero over time. Nevertheless, the consumer curve has a steeper slope and declines more rapidly than the government curve. This indicates that the evolution of consumer strategy occurs at a significantly faster rate than that of government strategy. The pattern suggests that when market conditions directly affect consumers' core interests, consumers tend to respond more sensitively and are quicker to adjust their strategic behaviour.

4.1.2 Analysis of low-cost R&D

As shown in Figure 2, while keeping the initial probabilities of consumers' preference for green energy (x), the government subsidy provision (y), and enterprises' "AI+ Green Energy" innovation (z) all at 0.5, without altering other parameter assignments, only the R&D cost C is reduced. Under this condition, the enterprise innovation probability curve shifts markedly, indicating that enterprises are firmly committed to "AI+ Green Energy" innovation. This highlights that R&D cost directly influences enterprises' decisions regarding "AI+ Green Energy" innovation.

Among the three curves, consumer responsiveness remains higher than that of the government and aligns closely with that of enterprises. This suggests that market regulation should place greater emphasis on consumer dynamics.

4.1.3 Analysis of green energy consumption identity

As shown in Figure 3, when consumers' social recognition benefit F increases and all other parameters remain consistent with the "Low-cost R&D" scenario, the government and enterprise curves stay largely unchanged, while the consumer curve undergoes a significant shift. This indicates that, after the benefits of consumers' social identity reach a certain threshold, their consumption behavior evolves over the course of time, thus demonstrating a stronger preference for consuming green energy.

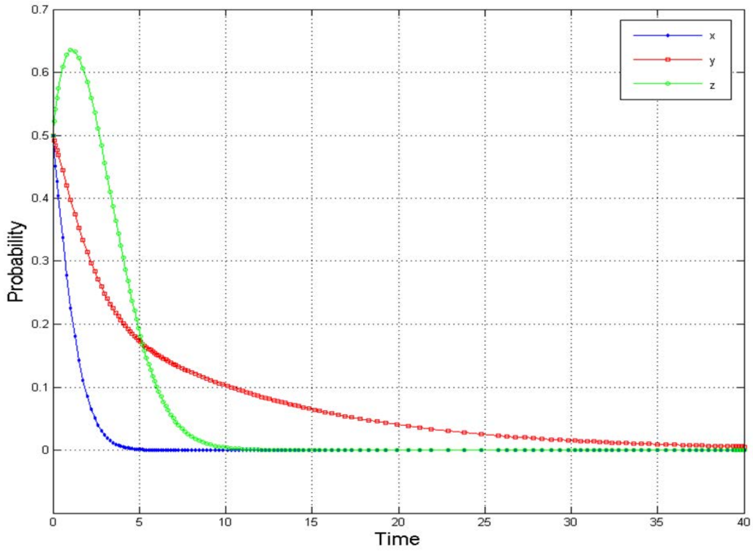

Figure 2. Evolutionary game analysis of low-cost R&D scenarios:
$F = 0.2; P_1 = 1; P_2 = 2; P_3 = 3; R_1 = 0.3; R_2 = 0.4; R_3 = 0.1; C = 0.1; H = 0.2; t = 0.1$

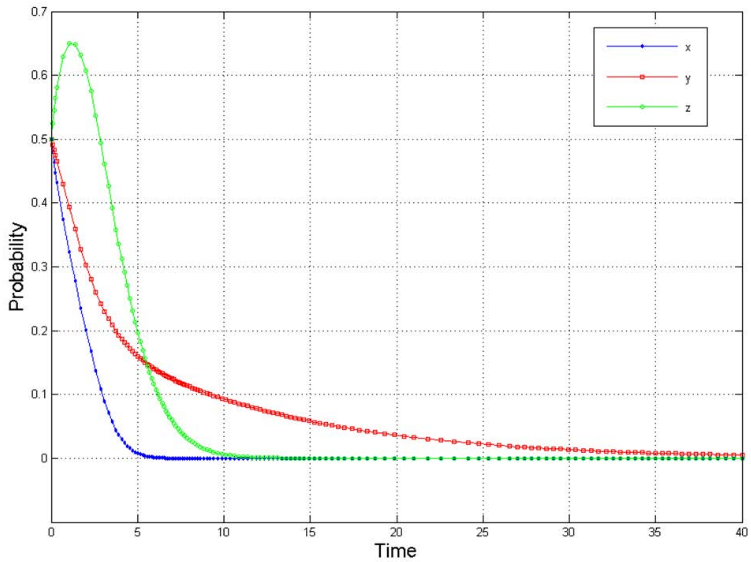

Figure 3. Evolutionary game analysis of green energy consumption identity:
$F = 1; P_1 = 1; P_2 = 2; P_3 = 3; R_1 = 0.3; R_2 = 0.4; R_3 = 0.1; C = 0.1; H = 0.2; t = 0.1$

4.2 Analysis of Different Probability Changes

Set different initial values of probability accordingly, Curve 1: $x = 0.3, y = 0.4, z = 0.5$; Curve 2: $x = 0.4, y = 0.5, z = 0.6$; Curve 3: $x = 0.5, y = 0.6, z = 0.7$.

4.2.1 Initial case analysis

As shown in Figure 4, despite initial differences in the probabilities of decision among consumers, governments, and enterprises, the evolutionary outcomes ultimately converge toward the same equilibrium, provided that the key external conditions remain unchanged.

4.2.2 Analysis of low-cost R&D

As shown in Figure 5, when the R&D cost is lowered, the evolutionary outcomes converge to the same equilibrium under identical external conditions. Although the final results of the evolutionary game are the same, the slopes of the three curves differ noticeably. This indicates that the evolutionary trajectories of consumers, governments, and enterprises vary according to their initial probability values.

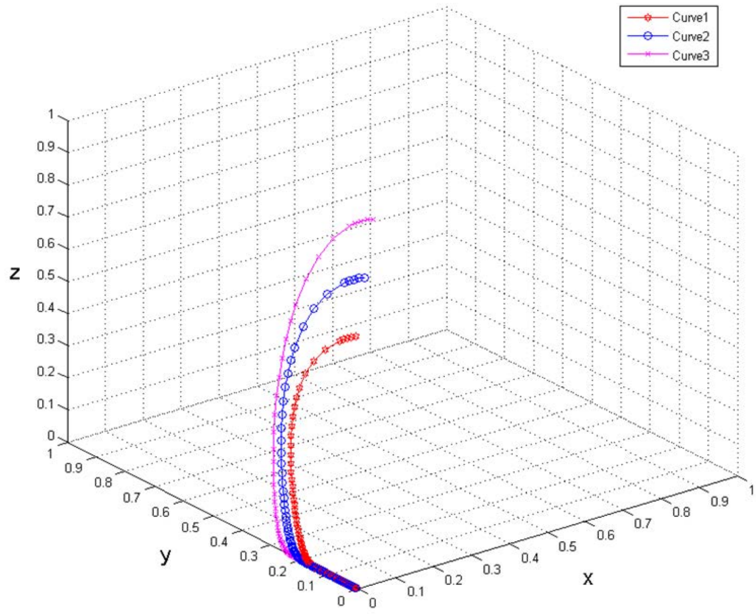

Figure 4. Three-dimensional evolutionary game analysis of the initial situation:
$F = 0.2; P_1 = 1; P_2 = 2; P_3 = 3; R_1 = 0.3; R_2 = 0.4; R_3 = 0.1; C = 0.5; H = 0.2; t = 0.1$

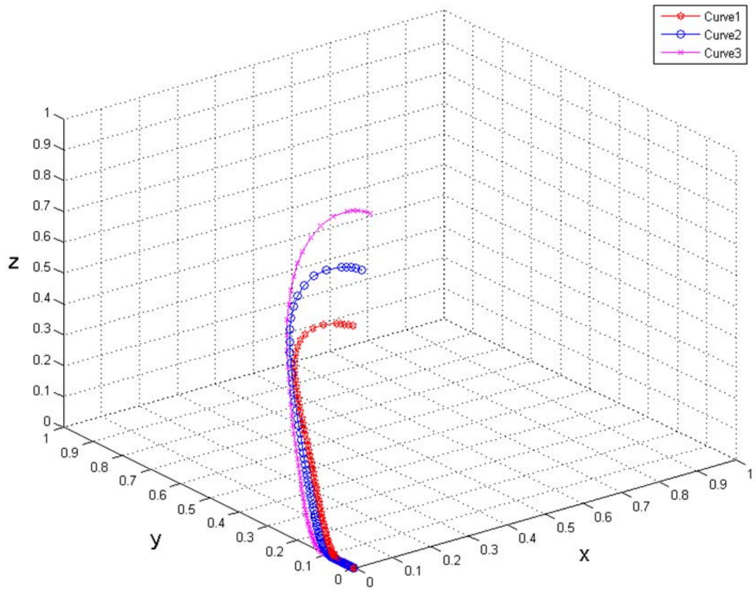

Figure 5. Three-dimensional evolutionary game analysis of low-cost R&D scenarios:
$F = 0.2; P_1 = 1; P_2 = 2; P_3 = 3; R_1 = 0.3; R_2 = 0.4; R_3 = 0.1; C = 0.1; H = 0.2; t = 0.1$

4.2.3 Analysis of green energy consumption identity

As shown in Figure 6, when benefits of consumers' social identity increase, the final equilibrium of the evolutionary game remains unchanged under the same external conditions. However, the evolutionary paths of the three parties continue to differ, depending on their initial probability values.

4.3 Discussion and Suggestions

4.3.1 Theoretical discussion

(1) Mechanism of AI Technology on Energy Efficiency, Innovation Capacity, and Cost Structure

AI technology significantly enhances the probability of "AI+ Green Energy" innovation by lowering R&D costs (C) and optimizing decision-making processes. As shown in the analysis, when R&D costs decrease from 0.5 to 0.1 (as in low-cost R&D scenarios), the enterprise innovation probability curve rises notably, indicating that AI can effectively reduce the threshold for innovation and improve the efficiency of R&D. Simultaneously, through big-data analytics of consumer preferences (x), AI enables enterprises to better match market demand, optimize energy system operations, and thus elevate overall energy efficiency. For instance, the evolution of "consumer green energy preference probability (x)" demonstrates that AI can accurately capture shifts in consumer behavior, thus guiding firms to adjust innovation strategies and creating a closed loop of "data insight → product optimization → efficiency enhancement".

(2) Pathway of Big-Data-Integrated AI in Green Energy Innovation

Big-data-integrated AI establishes a dynamic feedback mechanism linking "consumer behavior → policy response → enterprise innovation". By analyzing the game interactions among consumer preference (x), government subsidies (y), and enterprise innovation (z), AI technology allows enterprises to anticipate market changes and allocate R&D resources more effectively. The results indicated that under conditions of higher consumer recognition of green energy (e.g., $F = 1$), the consumer curve rose significantly, suggesting that AI-driven precision marketing can strengthen green consumption awareness and thereby stimulate corporate innovation. This "data perception → strategy adjustment → innovation output" pathway transforms green energy innovation from a reactive process into one that is proactively guided.

(3) Mechanism of the Influence of AI on Consumer Behavior and Market

AI technology shapes consumer behavior and enhances market efficiency through personalized recommendations and targeted marketing. The evolutionary rate of the consumer preference curve (x) is markedly higher than that of the government subsidy curve (x), indicating that consumers respond more sensitively to AI-personalized information. By analyzing behavioral data, AI can help optimize the deployment of policy instruments such as price discounts and green taxes. For example, in the "post-subsidy" era, AI can accurately identify levels of consumer anxiety and dynamically adjust subsidy strategies to maximize policy impact. This AI-enabled improvement in market efficiency shifts green energy consumption from being "policy-driven" to "demand-driven", fostering a virtuous cycle between market dynamics and technological advancement.

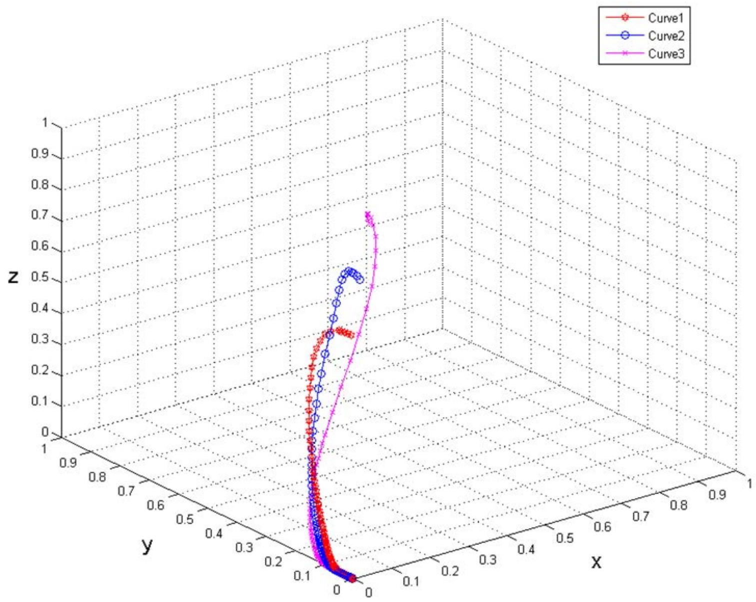

Figure 6. Three-dimensional evolutionary game analysis of green energy consumption identity: $F = 1; P_1 = 1; P_2 = 2; P_3 = 3; R_1 = 0.3; R_2 = 0.4; R_3 = 0.1; C = 0.1; H = 0.2; t = 0.1$

4.3.2 Relevant suggestions

(1) Lowering AI-Enhanced R&D Costs and Optimizing Innovation Incentive Policies

The low-cost R&D analysis indicates that reducing the R&D expenses of enterprises for "AI+ Green Energy" significantly enhances their willingness to innovate. The government could establish a dedicated "AI+ Green Energy" research fund, broaden the eligibility for applicants, and encourage small and micro-enterprises to actively compete for scientific funding, thereby lowering R&D costs through lump-sum research grants. Moreover, financial burdens can be alleviated by allowing research output to be exchanged for tax incentives. The government can also promote joint ventures between enterprises and research institutes to transform "AI+ Green Energy" innovation, in order to share both R&D outcomes and benefits of innovation. To further stimulate innovation, the government may launch a certification system for "AI+ Green Energy" demonstration enterprises or parks, providing financing or tax policy support to certified entities. This "point-to-area" approach can enhance overall corporate enthusiasm for "AI+ Green Energy" innovation.

(2) Focusing on Core Consumer Demand and Strengthening Green-Consumption Guidance Mechanisms

Based on the analysis of green energy consumption identity, the government can collaborate with stakeholders to design green energy consumption vouchers. Utilizing insights into "AI+ Green Energy" innovation and data about consumption habits, these vouchers can guide consumers toward sustainable energy habits. Campaigns raising public awareness can also educate consumers about linking utility of green energy with social recognition and tangible benefits. By employing big data about energy and AI-fusion technologies, the government could analyze temporal patterns in energy supply and implement more flexible time-based subsidy schemes. Therefore, the benefits of green energy consumption could become clearly perceptible to consumers. Given consumers' sensitivity to price, a unified green-energy pricing platform should be established to mitigate information asymmetry between consumers and enterprises. Moreover, green energy-themed promotional activities can be organized in high-traffic areas such as scenic spots and duty-free shops. Integrating these efforts with eco-tourism resources and incorporating green-consumption behavior into product discount policies could strengthen consumers' emotional identification with green energy consumption.

4.3.3 Dynamically adjusted government subsidy strategies and strengthened policy synergy

Based on the analysis of varying probability shifts, the government may implement proportional subsidies for early-stage green-energy enterprises and adopt tiered subsidy mechanisms for firms in the growth phase. This approach can guide enterprises toward achieving AI-enhanced green-energy innovation and development through market mechanisms. Furthermore, government support should evolve from subsidizing green-energy consumption and emission reduction toward thoughtful assistance that encompasses enterprises' R&D of AI-integrated green-energy products, marketing of green energy consumption, and consumer education.

Simultaneously, the government needs to adjust subsidy policies in a timely manner in accordance with the responses of green-energy enterprises and consumers. By linking subsidies to incentives for both enterprises and consumers, policy dividends can be effectively translated into market-driven behavior.

5 Conclusions and Prospects

This study elucidated a tripartite driving mechanism underlying AI-enabled green energy innovation, to offer a systemic policy framework for advancing a sustainable green economy. To incentivize corporate innovation, it is recommended to establish dedicated research funds for "AI+ Green Energy" initiatives, broaden eligibility for project applications for small and micro enterprises, and adopt lump-sum research funding mechanisms to effectively reduce R&D costs. Tax incentives should be associated with innovation outcomes, thus allowing substantial deductions on qualified R&D expenditures, and fostering collaborative innovation between firms and research institutions. Government subsidies must be calibrated to an appropriate level: too low risks encouraging rent-seeking behavior, while excessive support may crowd out firms' intrinsic investments in innovation. On the demand side, targeted "AI+ Green Energy" consumption vouchers should be designed based on the behavioral data to deliver personalized green messaging. Green energy awareness campaigns should be organized in high traffic areas such as tourist sites and duty-free zones, to achieve the purpose of linking green consumption with social recognition and tangible benefits. A unified green energy pricing platform is also essential to mitigate information asymmetry, complemented by flexible and data-driven time-of-use subsidy schemes. Collectively, these measures could shift green energy adoption from policy-driven to demand-driven dynamics, thus establishing a closed-loop system of "data sensing $\rightarrow$ strategic adjustment $\rightarrow$ innovation enhancement". This approach provides an actionable pathway toward a fair, efficient, and coordinated green economic system.

However, this study has certain limitations as the assumptions of the model do not fully capture the nonlinear characteristics of real-world systems. Based on the findings and shortcomings, future research could further explore these dynamics. Subsequent research could concentrate on the deep integration of AI and green energy, with a focus on developing a data-aware intelligent energy pricing platform and personalized consumption voucher algorithms. This would help construct a synergistic closed loop involving "policy, enterprise, and demand," thereby providing an intelligent solution for a sustainable economic system.

Author Contributions

Conceptualization, S.Q.T.; methodology, S.Q.T.; investigation, S.Q.T.; validation, S.Q.T.; visualization, S.Q.T.; writing—original draft preparation, S.Q.T.; resources, T.T.W.; writing—review and editing, T.T.W.; project administration, T.T.W. All authors have read and agreed to the published version of the manuscript.

Data Availability

This study is in the stage of theoretical research, and the data used are example data.

Conflicts of Interest

The authors declare no conflict of interest.

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