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How Does Mental Accounting Affect Green Technology Diffusion Among Construction and Demolition Waste Recycling Enterprises? An Evolutionary Analysis on a Scale-Free Network

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Abstract

Green technology can improve construction and demolition waste recycling, yet an objective payoff advantage does not necessarily lead to sustained adoption. This study examines how enterprise valuation and network learning jointly shape diffusion. A rational benchmark model, a prospect theory–mental accounting model, and a mental accounting–hedonic editing model are developed on a Barabási–Albert scale-free network, with strategy updates governed by a Fermi rule based on neighborhood-relative rankings. Under the baseline conditions, separate account evaluation weakens the perceived advantage of green technology, and local imitation amplifies this difference into low adoption. Hedonic editing improves the relative performance of green technology by comparing integrated and separate evaluations, while its diffusion effect remains conditional on underlying revenues and costs. Across the parameter ranges examined, technological maturity supports diffusion by reducing production costs and research and development risk. Initial adoption and average network degree jointly affect the spread of advantageous strategies. Subsidies and penalties lower adoption thresholds, but higher adoption does not guarantee higher average enterprise net payoffs. These findings connect objective payoffs, account-based valuation, and network diffusion, informing integrated project appraisal, demonstration programs, and policy-mix design.

Keywords: construction and demolition waste recycling; green technology diffusion; mental accounting; hedonic editing; complex networks

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1. Introduction

The rapidly increasing volume of construction and demolition waste (CDW) intensifies pressure on urban solid waste management systems and scarce land resources. It also highlights the importance of recycling construction materials to reduce demand for virgin resources [1,2]. Sorting, crushing, screening, and property enhancement can convert some CDW into recycled construction materials. However, variable feedstock composition, inconsistent product quality, high upfront investment, and limited market acceptance continue to affect the operating performance of recycling projects [3,4]. Green technology can improve material recovery rates and recycled product performance. Its diffusion nevertheless depends on technological maturity, research and development (R&D) risks, market returns, and policy conditions [4,5].

Existing studies mainly explain technology choices among CDW recycling enterprises through techno-economic conditions and the external institutional environment. Technological maturity affects processing efficiency and product quality. Government subsidies help cover R&D and equipment investment, while environmental regulation increases the relative cost of conventional technology. Quality standards, green procurement, and information disclosure can strengthen market expectations for recycled products [6–8]. However, these external and internal conditions affect adoption only after enterprises incorporate them into their valuation processes. Differences in information access, budgeting, and risk perception can lead enterprises to evaluate the same project differently. Actual adoption may therefore remain limited even when green technology offers an objective net payoff advantage [9,10]. Explaining this discrepancy requires linking economic returns to enterprise valuation.

Prospect theory (PT) provides a basis for examining technology choices under bounded rationality. PT suggests that decision-makers evaluate gains and losses relative to a reference point rather than solely in terms of final wealth. The value function is also steeper for losses than for gains [11,12]. In green technology investment, enterprises may treat their current operating conditions or historical performance as reference points. These benchmarks shape their subjective evaluations of equipment investment, R&D risks, subsidy income, and green product revenues [10,13,14]. A technology with a positive objective net payoff may therefore have a different perceived value. The revenue–cost structure and the selected reference points jointly determine both the direction and magnitude of this valuation difference.

Mental accounting (MA) further suggests that decision-makers do not combine all economic outcomes into a single account. Instead, they allocate outcomes to different accounts according to their source, purpose, or timing. Fungibility across these accounts is limited [15–20]. When evaluating green technology, CDW enterprises may assign product revenues and policy subsidies to a benefit account, while assigning equipment investment and R&D risks to a cost account. Enterprises then evaluate each account separately through the PT value function. The perceived project value thus depends not only on its objective net payoff but also on how benefits and costs are coded. MA does not imply that enterprises disregard profit. Rather, it explains why the same economic information can lead to different decisions under different accounting boundaries.

Beyond account classification, MA also addresses how multiple outcomes are combined and presented. This process is described by hedonic editing (HE) [15,16]. HE allows enterprises to evaluate benefits and costs separately or integrate them into an overall net change for the project. Enterprises can then adopt the coding method that produces the greatest perceived utility. HE does not alter objective project cash flows. However, it can change the relative salience of costs and benefits in decision-making. Incorporating HE may therefore change enterprise assessments of green technology. Existing MA research has focused mainly on consumption, payment, saving, and travel choices [18–20]. Research has devoted considerably less attention to enterprise-level green technology adoption and the subsequent diffusion of that technology across an industry.

CDW recycling enterprises do not operate in isolation. Through project collaboration, equipment procurement, technical consultation, and market competition, they observe the technological performance of other enterprises and adjust their own choices. Real-world industrial networks often exhibit heterogeneous connectivity. A small number of enterprises maintain many collaborative relationships, whereas most have relatively few connections. A BA scale-free network can approximate this feature [21,22]. Enterprises generally lack complete information on their neighbors' costs and profits. However, they can more readily identify relative operating performance. Previous research indicates that payoff-ranking-based Fermi rules can represent strategy learning from relative positions under limited information [23]. Compared with direct comparisons of absolute payoffs,

local rankings reduce the influence of differences in payoff scales on imitation probabilities. They also more closely represent how enterprises adjust decisions in response to the relative performance of their peers.

Existing research provides important foundations in CDW recycling policy, behavioral decision-making, and network diffusion. However, these strands remain insufficiently integrated. Most CDW studies explain technology adoption using objective costs and benefits [7–9]. Studies incorporating PT mainly examine aggregate value changes, with limited attention to account segregation and HE within MA [9,10,13,14]. Network diffusion studies typically model learning using absolute payoff differences. A unified framework is still needed to explain how different account-based evaluations generate industry-level adoption differences through local rankings [14,23,24].

To address this gap, this study develops three models of green technology diffusion among CDW recycling enterprises on a Barabási–Albert (BA) scale-free network: a rational benchmark model (RM), a prospect theory–mental accounting model (PT-MA), and a mental accounting–hedonic editing model (MA-HE). All three models use the same objective revenue–cost structure and strategy update mechanism. The analysis addresses three questions:

1. How does separate account evaluation in PT-MA affect the diffusion trajectory of green technology?
2. How do changes in account coding after introducing HE affect the relative performance of green technology and its diffusion outcomes?
3. How do technological maturity, initial adoption, network connectivity, and policy instruments affect diffusion conditions under different decision models?

This study makes three contributions. First, it incorporates account segregation, dynamic reference points, and HE into enterprise technology diffusion. This reveals the behavioral mechanisms through which objective payoff advantages translate into adoption. Second, it connects enterprise cognition with network learning through neighborhood-relative performance. This provides a common mechanism for comparing different forms of perceived value. Third, it examines technological, market, network, and policy scenarios to distinguish the effects of techno-economic conditions from those of valuation. The results provide practical guidance for integrated project appraisal, technology demonstration programs, and coordinated policy design.

The remainder of this paper is organized as follows. Section 2 reviews research on green innovation in CDW recycling, behavioral decision-making, and diffusion in complex networks. Section 3 presents the assumptions, the three models, and the strategy update mechanism. Section 4 reports the simulation results. Section 5 presents the conclusions.

2. Literature Review

2.1. CDW Recycling and Green Technology Adoption

CDW recycling involves source separation, collection and transportation, pretreatment, reprocessing, and product application. Its effectiveness depends on feedstock composition, processing scale, equipment capacity, product performance, and quality standards [2,3]. Under suitable processing and application conditions, recycled aggregates and recycled concrete can replace some virgin materials. However, impurities, differences in material sources, and performance variability increase the requirements for production control and quality certification [2,6]. Green technology adoption therefore involves equipment investment, sorting processes, R&D trials, quality testing, and the capacity to bring products to market. Technological improvements can increase material recovery rates and product

value. They also require substantial upfront investment, organizational adjustment, and uncertainty over investment recovery [4,6].

The determinants of green technology adoption include technological, organizational, and institutional conditions. Enterprise size, accumulated technological capabilities, R&D capacity, and management experience provide the internal foundation. Environmental regulation, government subsidies, market demand, industry standards, and supply chain collaboration provide external incentives and constraints [4,5]. CDW research also shows that waste management and recycling projects depend on feedstock supply, product quality, project scale, and stakeholder collaboration [7,8]. Collectively, these conditions determine technological feasibility and operating returns. They also provide an economic basis for examining how enterprises perceive and compare project value.

2.2. Prospect Theory, Mental Accounting, and Hedonic Editing

Researchers have applied PT to explain reference dependence and loss aversion in risky investment, consumption choices, supply chain management, travel behavior, energy transitions, and environmental governance [11,12]. These studies compare actual outcomes with expected conditions to examine responses to improved returns, rising costs, and changing risks. Transport research focuses on reference dependence in travel time and monetary costs. Energy and environmental governance studies examine strategy adjustments under uncertain returns and different policy conditions [10,13,14]. These findings demonstrate that subjective valuation mediates the effect of objective economic outcomes on behavior. The resulting evaluations depend on reference points and the value function.

Building on reference dependence in PT, MA emphasizes account formation, the non-fungibility of funds, and budget boundaries. Thaler [15,16] proposed that decision-makers establish relatively independent accounts according to the source and intended use of funds. Heath et al. [25] found that mental accounting frames affect the evaluation of price changes. Cheema and Soman [18] and Antonides et al. [19] demonstrated the behavioral effects of account boundaries through account flexibility and household budgeting, respectively. Koch and Nafziger [20] further linked MA to goal setting and decision bracketing. Their work suggests that account segregation can affect organizational and intertemporal decisions as well as consumer behavior. For CDW enterprises, equipment investment, R&D expenditure, policy subsidies, and recycled product revenues may belong to different budgetary or managerial categories. Simply aggregating these items into net payoffs may overlook cognitive differences in actual adoption decisions.

HE is an MA mechanism for coding and combining multiple outcomes. Its application varies across decision contexts [15,16]. Liu et al. [26] compared PT-TC, MA-TC, and MA-HE models in travel choice. They found that the explanatory power of the original HE principles differed between deterministic and risky settings. HE therefore does not universally improve or hinder decisions. Instead, it changes how benefits and costs enter the valuation process.

2.3. Green Technology Diffusion in Complex Networks

Innovation diffusion depends not only on independent enterprise decisions but also on information transmission, social learning, and network structure. Complex network research shows that degree distributions, clustering, and path lengths affect the speed of information transmission and opportunities for repeated exposure [21,22,27]. Network ties can reduce information search costs and strengthen demonstration effects. They can also transmit accounts of failure or create local lock-in [28]. Consequently, greater network connectivity does not necessarily increase final adoption. Its effect depends on the technology choices of central nodes and the nature of the information transmitted.

In addition to network structure, the use of local information is critical to diffusion outcomes. The conventional Fermi rule determines imitation probabilities from precisely comparable absolute payoff differences between two agents [29]. Enterprises, however, often lack complete information on their peers' costs and profits. Their relative operating positions are easier to identify. Liu and Li [23] linked MA with rank-based strategy updating. Their findings indicate that local rankings can translate payoff levels into relative performance under limited information. Accordingly, this study replaces absolute payoff comparisons with a Fermi update rule based on neighborhood-relative rankings.

2.4. Research Gap and Contributions

CDW research has extensively identified the technological, market, and policy conditions affecting green technology adoption. PT and MA research has revealed the effects of reference points, account coding, and outcome integration on behavioral choices. Complex network research has clarified the roles of local interactions and connectivity in technology diffusion. However, few studies compare objective net payoffs, separate mental account evaluation, and perceived value under HE within a unified CDW recycling context. Limited attention has also been paid to how these valuation differences generate industry-level diffusion outcomes through local enterprise learning. This study therefore develops RM, PT-MA, and MA-HE on a BA scale-free network. A Fermi update mechanism based on neighborhood-relative performance connects techno-economic conditions, enterprise cognition, and network diffusion.

3. Model Assumptions and Construction

3.1. Problem Description

Consider a green technology innovation network comprising N CDW recycling enterprises. Each enterprise chooses either green technology or conventional technology. Enterprises update their strategies in each period according to their current performance and their rankings relative to neighboring enterprises. Connections are represented by a BA scale-free network. Once generated, the network structure remains fixed, while enterprise strategies evolve over time.

To examine the effects of different decision approaches on technology diffusion, this study develops RM, PT-MA, and MA-HE under identical objective revenue–cost structures, policy conditions, network structures, and update rules. Comparisons across these models reveal how cognition and account coding affect the diffusion trajectories and evolutionary outcomes of green technology in CDW recycling.

3.2. Basic Assumptions

3.2.1. Network and Strategies

Recycling enterprises are the main participants in green technology innovation. Undirected edges represent information exchange, technological collaboration, and competitive relationships. The industry contains a small number of highly connected core enterprises and many enterprises with relatively few connections. A BA scale-free network is therefore used to represent heterogeneous connectivity [21,22].

At initialization, strategies are randomly assigned according to the initial adoption proportion φ_0. Enterprises then engage in imitation learning through a locally rank-based Fermi rule until the strategy distribution stabilizes. An enterprise cannot use both technologies simultaneously or change its strategy more than once within a period [24].

3.2.2. Costs, Revenues, and Risks

The production costs of construction materials using green and conventional technologies are denoted by C_g and C_t, respectively, with $C_g > C_t$ [4,6]. The baseline revenue from conventional technology is E. Consumer preferences for green products increase the revenue of green technology users to $(1 + \nu)E$. Here, ν is the revenue premium coefficient, with $0 < \nu < 1$.

Green technology innovation involves R&D risks. The model links the associated losses to the green production cost C_g and technological maturity δ through the relationship $C_g = C_{g0}e^{-\delta}$, where $0 < \delta < 1$. Conventional technology is assumed to be mature. Its production cost is relatively insensitive to the enterprise's technological development level, so this source of variation is excluded.

The risk loss associated with green technology, K, decreases nonlinearly with technological maturity; that is, $K = K_0e^{-\delta}$ [10].

Enterprises can reduce R&D risks through communication and collaboration. These activities require an expenditure F. As the proportion of green technology adopters, φ, increases, this expenditure declines nonlinearly as $F = F_0e^{-\varphi}$.

Here, K_0 and F_0 denote the baseline risk loss and baseline communication expenditure, respectively.

3.2.3. Subsidies and Penalties

The government provides a subsidy S to green technology adopters and imposes an environmental penalty P on enterprises that continue to use conventional technology [7,8]. The subsidy decreases as the green technology adoption proportion rises and is given by $S = s(1 - \varphi)$, where s denotes subsidy intensity. The environmental penalty remains constant as an additional cost of conventional technology. Enterprises assign subsidies to the benefit account and penalties to the cost account.

3.2.4. Mental Account Evaluation

In RM, enterprises evaluate their current strategies using objective net payoffs. In PT-MA, they establish separate benefit and cost accounts. They then use the PT value function to calculate perceived values relative to reference points. In MA-HE, enterprises further compare integrated and separate account coding and select the approach that yields higher perceived utility.

To isolate the account-coding mechanism, the model excludes multiple probability branches and probability weighting functions. Both mental accounts use the same value-function parameters [12,26]. The value function is given in Equation (1):

$$V(x) = \begin{cases} x^{\alpha}, & x \geq 0, \\ -\lambda(-x)^{\alpha}, & x < 0. \end{cases} \quad (1)$$

In Equation (1), x is the outcome entered into the value function after comparison with the relevant reference point. The parameter α captures the curvature of the value function and is referred to here as the risk preference coefficient. The parameter λ is the loss aversion coefficient.

3.2.5. Dynamic Reference Points

Boundedly rational enterprises use their actual benefit and cost account values from the preceding period as current reference points. Fixed exogenous reference values are not used. This assumption reflects the adjustment of performance expectations to recent operating outcomes. Enterprises assess improvements or deteriorations relative to their own historical conditions [30,31].

No historical operating information is available at initialization. All enterprises therefore use the benefit and cost account values associated with conventional technology as their initial reference points.

Specifically, the reference points for enterprise i at time t are its actual benefit account value M_i^{t-1} and cost account value T_i^{t-1} at time $t-1$. If enterprise i used green technology in the preceding period, these values are given by Equations (2) and (3):

$$M_i^{t-1} = (1+\nu)E + S, \tag{2}$$

$$T_i^{t-1} = C_g + K + F. \tag{3}$$

If enterprise i used conventional technology in the preceding period, the corresponding values are given by Equations (4) and (5):

$$M_i^{t-1} = E, \tag{4}$$

$$T_i^{t-1} = C_t + P. \tag{5}$$

At $t = 0$, all enterprises share the initial reference values specified in Equations (6) and (7):

$$M_i^0 = E, \tag{6}$$

$$T_i^0 = C_t + P. \tag{7}$$

3.3. Rational Benchmark Model

In RM, recycling enterprises are assumed to be fully rational and to evaluate strategies according to objective net payoff maximization. The perceived payoff U_i of enterprise i is identical to the objective net payoff generated by its strategy.

When an enterprise does not adopt green technology, its objective net payoff is given by Equation (8):

$$A = E - C_t - P. \tag{8}$$

When an enterprise adopts green technology, its objective net payoff is given by Equation (9):

$$B = (1+\nu)E - C_g - K - F + S. \tag{9}$$

Thus, $U_i = A$ for conventional technology users and $U_i = B$ for green technology adopters.

3.4. Prospect Theory–Mental Accounting Model

PT-MA introduces bounded rationality. Enterprises evaluate gains and losses through separate mental accounts using the PT value function. The reference points of enterprise i at time t are defined as $M_{i0}^t = M_i^{t-1}$ and $T_{i0}^t = T_i^{t-1}$.

If enterprise i adopts green technology, its benefit and cost account values are given by Equations (10) and (11):

$$M_i = (1+\nu)E + S, \tag{10}$$

$$T_i = C_g + K + F. \tag{11}$$

If enterprise i uses conventional technology, its account values are given by Equations (12) and (13):

$$M_i = E, \tag{12}$$

$$T_i = C_t + P. \tag{13}$$

The changes in the benefit and cost accounts are evaluated using Equations (14) and (15), respectively:

$$V(\Delta M) = \begin{cases} (\Delta M)^{\alpha}, & \Delta M \geq 0, \\ -\lambda|\Delta M|^{\alpha}, & \Delta M < 0, \end{cases} \tag{14}$$

$$V(-\Delta T) = \begin{cases} (-\Delta T)^{\alpha}, & \Delta T \geq 0, \\ -\lambda|\Delta T|^{\alpha}, & \Delta T < 0. \end{cases} \tag{15}$$

The account changes relative to the reference points are defined in Equations (16) and (17):

$$\Delta M = M_i - M_{i0}^t, \tag{16}$$

$$\Delta T = T_i - T_{i0}^t. \tag{17}$$

Without HE, the perceived payoff of enterprise i is the sum of the two account utilities, as specified in Equation (18):

$$U_i = V(\Delta M) + V(-\Delta T). \tag{18}$$

3.5. Mental Accounting–Hedonic Editing Model

MA-HE extends PT-MA by introducing the HE criterion. Enterprise decision-makers choose the way of combining account outcomes that yields the greatest subjective utility. The reference points are identical to those in PT-MA.

HE allows two evaluation approaches: integration and segregation. Under integrated evaluation, the perceived payoff of enterprise i is expressed in $V(\Delta M - \Delta T)$. Under separate evaluation, the perceived payoff is expressed in $V(\Delta M) + V(-\Delta T)$.

The integrated value function takes the piecewise form shown in Equation (19):

$$V(\Delta M - \Delta T) = \begin{cases} (\Delta M - \Delta T)^{\alpha}, & \Delta M - \Delta T \geq 0, \\ -\lambda|\Delta M - \Delta T|^{\alpha}, & \Delta M - \Delta T < 0. \end{cases} \tag{19}$$

Decision-makers select the evaluation approach that provides higher psychological utility. The perceived payoff of enterprise i is therefore given by Equation (20):

$$U_i = \max[V(\Delta M - \Delta T),\ V(\Delta M) + V(-\Delta T)]. \tag{20}$$

In Equation (20), $V(\Delta M - \Delta T)$ and $V(\Delta M) + V(-\Delta T)$ represent utilities under integrated and separate evaluation, respectively.

3.6. Evolutionary Rules for Enterprise Strategies on the Network

The network-generation process begins with a small connected network. At each growth step, a new node is introduced and connected to existing nodes. Connections follow preferential attachment: nodes with higher degrees are more likely to receive new links and establish interaction relationships. The growth process continues until the network reaches the prescribed number of enterprises.

The probability that a new node connects to an existing node i is given by Equation (21):

$$p(i) = \frac{d_i(t)}{\sum_{j=1}^{N} d_j(t)}. \tag{21}$$

Here, $d_i(t)$ is the degree of enterprise i at time t. The denominator represents the total degree of the nodes present at that growth step.

This study uses a local rank-based strategy update rule. Prior research motivates the use of rank-based comparisons rather than direct payoff differences in the conventional Fermi

rule [23]. Enterprises compare their relative positions based on perceived payoffs instead of comparing perceived payoff levels alone. The MA value function exhibits diminishing sensitivity to gains. As outcomes increase, additional gains generate progressively smaller increments in perceived value. Relative position within a group therefore provides an appropriate basis for representing enterprise comparisons.

The normalized local rank of enterprise i is defined in Equation (22):

$$R_i(t) = \frac{\sum_{k \in L_i} 1[U_k(t) < U_i(t)] + \frac{1}{2} \sum_{k \in L_i} 1[U_k(t) = U_i(t)]}{d_i}. \quad (22)$$

In Equation (22), L_i denotes the set of neighbors of enterprise i, and $1[\cdot]$ is the indicator function. A larger $R_i(t)$ indicates better perceived performance relative to the enterprise's neighbors. Ties receive a weight of one-half.

This formulation reflects peer comparison and competitive pressure in enterprise decision-making. When considering technological innovation, enterprises assess both their own payoffs and the relative performance of other enterprises. The probability that enterprise i imitates neighbor j is given by Equation (23):

$$W_{i \to j} = \frac{1}{1 + \exp\left(-\frac{R_j - R_i}{\kappa}\right)}. \quad (23)$$

Here, R_i and R_j are the neighborhood-relative rankings of enterprise i and its neighbor j in the current round. The parameter κ controls sensitivity to ranking differences. A smaller κ produces a stronger response to a higher-ranked neighbor [31]. As iterations increase, the network topology remains unchanged; the enterprise policy proportion gradually converges or fluctuates near the steady state.

4. Numerical Simulations and Discussion

4.1. Parameter Settings

The scale-free network contains $N = 100$ enterprises and has an average degree of $d = 4$. All monetary quantities are expressed in a common normalized unit. The baseline revenue of conventional technology is set to $E = 10$ as the numeraire. The corresponding conventional production cost is $C_t = 6$. Green technology adopters receive a revenue premium of $\nu = 0.5$. Their baseline production cost is $C_{g0} = 10$, baseline risk loss is $K_0 = 6$, and baseline communication expenditure is $F_0 = 1$. These values are set with related studies [14,32,33], as well as the operating data of an actual recycling project in Chengdu, Sichuan Province. Technological maturity is set to $\delta = 0.35$ and is used to calculate the exponential decay of actual production costs and risk losses [34].

The government provides a subsidy with intensity $s = 1.5$ to green technology adopters. It imposes a penalty of $P = 1$ on conventional technology users. These are based on the policy context in related studies [35] and are examined in the sensitivity analysis in Appendix A, Table A1. In addition, Appendix A provides a one-at-a-time sensitivity check for key economic and policy parameters, examining the stability of the model comparison around the baseline setting and supplementing the diffusion outcome analysis under alternative parameter conditions. The initial green technology adoption proportion is $\varphi_0 = 0.3$.

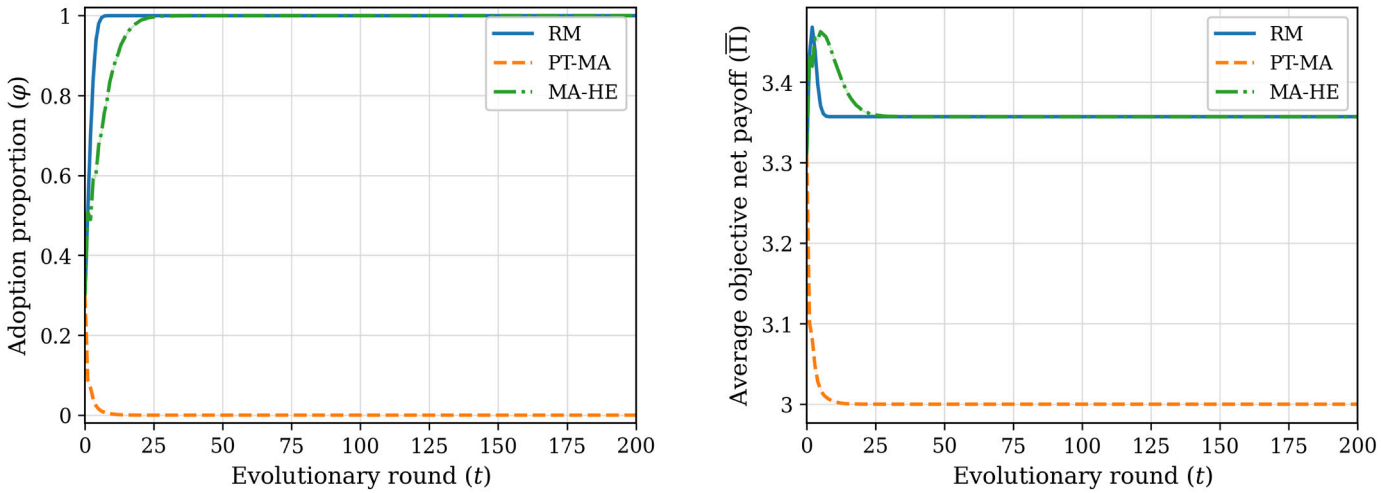
For comparability across models, the risk preference coefficient is fixed at $\alpha = 0.88$ and the loss aversion coefficient at $\lambda = 2.25$ [12]. The ranking sensitivity parameter is set to $\kappa = 0.1$ [31].

Each parameter combination is evaluated using 500 independent simulations, with 200 rounds per simulation. A new network, initial strategy assignment, and random update sequence are generated for each simulation. Outcomes are reported as means across the

500 simulations. Steady-state outcomes are calculated by first averaging results from rounds 181–200 within each simulation and then aggregating these values across simulations.

4.2. Baseline Comparison of RM, PT-MA, and MA-HE

Figure 1 compares the green technology adoption proportion and average enterprise net payoff across RM, PT-MA, and MA-HE under the baseline parameter settings. Panel (a) presents the adoption proportion, and panel (b) presents the average enterprise net payoff.



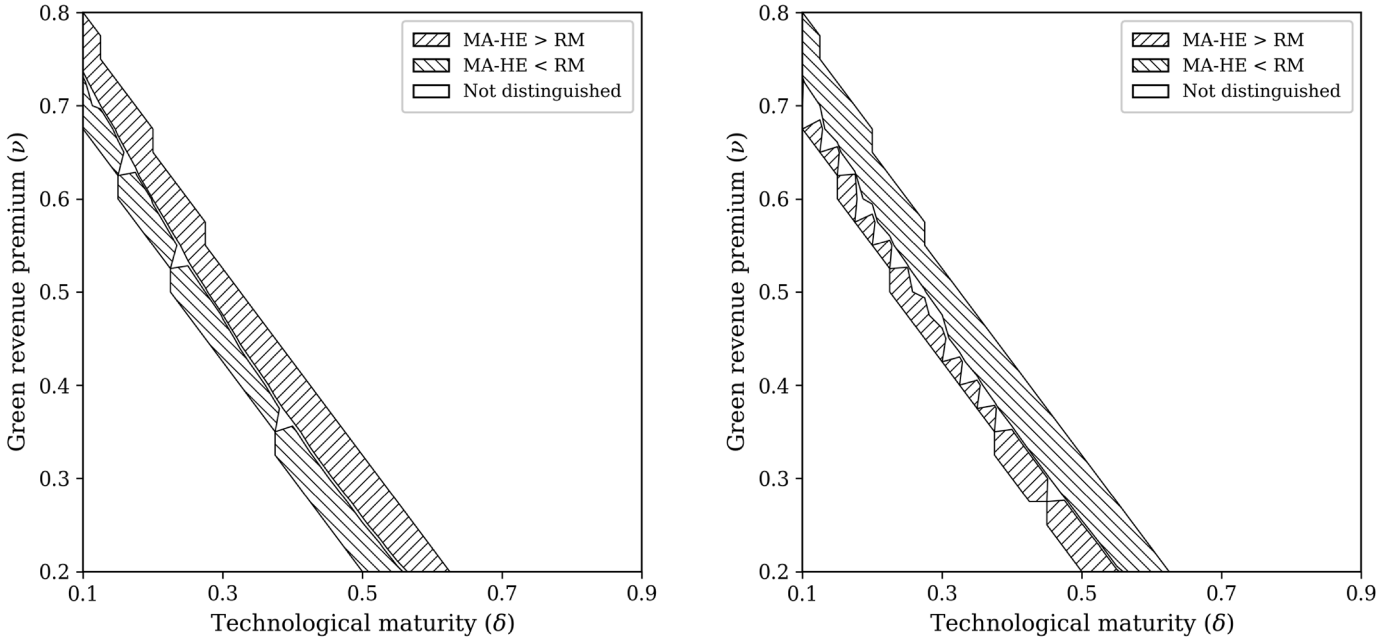
(a) (b)

Figure 1. Effects of the three models on green technology adoption and average enterprise net payoff: (**a**) adoption proportion; (**b**) average enterprise net payoff.

Figure 1 shows that enterprise valuation can substantially change diffusion outcomes even when the objective payoff structure is identical. RM compares objective net payoffs. Green technology has a relative payoff advantage and therefore gradually diffuses. PT-MA evaluates benefits and costs separately. Loss aversion amplifies the perceived burden of upfront costs and R&D risks. This places green technology adopters at a disadvantage in local rankings and ultimately inhibits diffusion.

MA-HE compares integrated and separate coding. It enables enterprises to evaluate green technology in terms of overall project outcomes, reducing the influence of an isolated cost account on decisions. Both adoption and average net payoffs are higher than in PT-MA. Under these conditions, HE does not encourage enterprises to adopt a low-return technology. Instead, it helps them recognize an existing objective net payoff advantage.

Under the baseline setting, RM and MA-HE follow almost the same diffusion path. We therefore plot Figure 2 to identify the conditions under which MA-HE departs from RM, comparing terminal adoption and average objective net payoff over a two-parameter grid: technological maturity, $\delta \in [0.10, 0.90]$, and green revenue premium, $v \in [0.20, 0.80]$, with a step of 0.025 and all other parameters at baseline. Each grid point uses independent replications; reported values are terminal means. Classification uses the 95% confidence interval of the mean difference between MA-HE and RM. The results are classified as: entirely above zero (i.e., Model MA-HE > Model RM), entirely below zero (i.e., Model MA-HE < Model RM), and an interval including zero (i.e., Not distinguished).



(a) (b)

Figure 2. Differences between MA-HE and RM across technological maturity and the green revenue premium: (**a**) steady-state adoption proportion; (**b**) average enterprise net payoff. **Note:** MA-HE and RM denote the two models. MA-HE > RM (or MA-HE < RM) indicates the mean value of MA-HE is significantly greater (or lower) than that of RM.

Figure 2 shows that the difference between MA-HE and RM is concentrated along a diagonal diffusion-threshold band. The threshold band extends from the low-maturity and high-premium region to the higher-maturity and lower-premium region. In Figure 2a, the difference appears along this band. For example, when δ is close to 0.10, the model difference appears mainly when v is approximately 0.70–0.80. When δ is close to 0.30, the difference shifts to approximately $v = 0.45 - 0.55$. This pattern indicates that a higher level of technological maturity reduces the green revenue premium required for diffusion.

Figure 2b reports the corresponding comparison for average enterprise net payoff. The distinguishable region again follows this band. Most of the parameter space is blank. This means that MA-HE and RM are not statistically distinguished when the system is far from the threshold. This result is consistent with the baseline comparison in Figure 1. When green technology has a clear objective net-payoff advantage, both models converge to high adoption. When the revenue premium is insufficient to compensate for the cost and risk burden, both models converge to low adoption. The incremental effect of HE is therefore most visible when enterprises are close to strategic indifference. In this region, the recombination of gain and loss accounts changes the perceived attractiveness of green technology. It shifts the diffusion boundary and affects both steady-state adoption proportion and average enterprise net payoff.

4.3. Effects of Technological Maturity and the Green Revenue Premium

To clarify the economic source of this threshold, technological maturity and green revenue premium are varied separately, while all other parameters are fixed at their baseline values. The results are presented in Figures 3 and 4. The shaded bands denote 95% confidence intervals. In several parameter ranges, the confidence bands are narrow and are largely covered by the lines and markers.

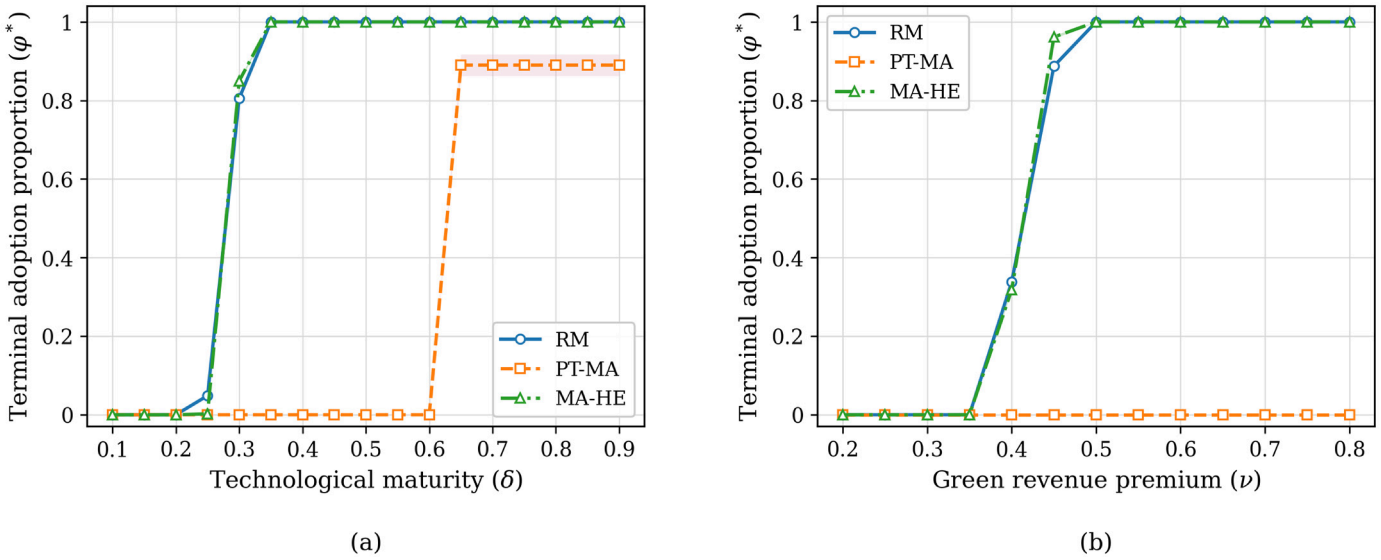


Figure 3. Effects of technological maturity and the green revenue premium on steady-state adoption: (**a**) technological maturity; (**b**) green revenue premium. **Note:** The asterisk (*) indicates the steady-state value of this parameter.

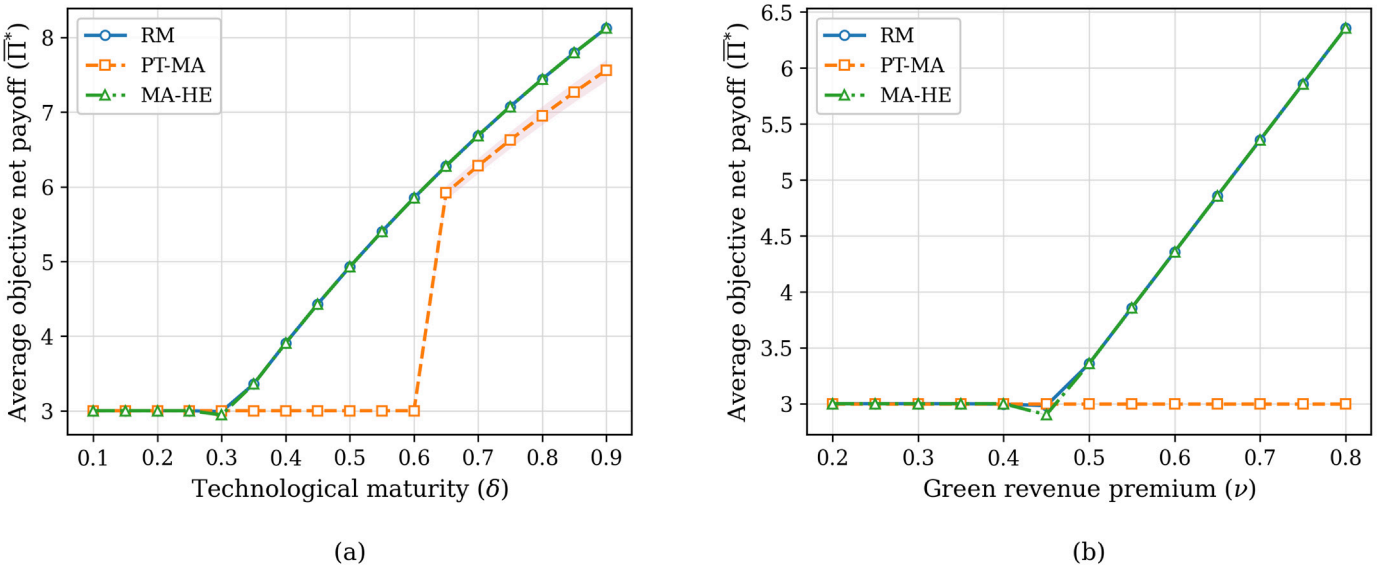


Figure 4. Effects of technological maturity and the green revenue premium on average enterprise net payoff: (**a**) technological maturity; (**b**) green revenue premium. **Note:** The asterisk (*) indicates the steady-state value of this parameter.

Figure 3 shows clear diffusion thresholds for both technological maturity and the green revenue premium. As technological maturity increases, green production costs and R&D risks decline. Once green technology adopters gain an advantage in local rankings, neighborhood imitation rapidly amplifies it. RM and MA-HE reach high-adoption states at lower maturity levels. When δ is about 0.30, their terminal adoption proportions are close to 0.80. When δ increases to about 0.35, both models reach full adoption. PT-MA requires greater technological maturity to overcome perceived losses in the cost account. Its terminal adoption proportion remains 0 when δ is below about 0.60, and increases to about 0.89 when δ reaches about 0.65. Local fluctuations near the thresholds mainly reflect finite network size, stochastic imitation, and absorbing states.

A higher green revenue premium also promotes diffusion. Under RM and MA-HE, adoption remains close to 0 when v is below about 0.35. It increases to about 0.33 when v

reaches about 0.40, and rapidly approaches full adoption when v enters the range of 0.45–0.50. Under PT-MA, green technology does not diffuse within the examined range of v, and the terminal adoption proportion remains 0. This indicates that the green revenue premium operates mainly through the benefit account. Its improvement of PT-MA outcomes is therefore weaker than that of technological maturity within the parameter ranges examined. Unlike an increase in product prices alone, technological maturity reduces both production expenditure and R&D risks. It thus more directly alleviates the cost burden of green technology.

Figure 4 shows that green technology adoption and average enterprise net payoffs do not always increase together. As technological maturity increases, the average enterprise objective net payoff under RM and MA-HE rises after the diffusion threshold is crossed. When δ is below about 0.30, the payoff is close to 3.00. When δ increases to about 0.50, the payoff is about 4.9. When δ reaches 0.90, the payoff increases to about 8.1. Under PT-MA, the payoff remains close to 3.00 when δ is below about 0.60. After the maturity threshold is crossed, the payoff increases with adoption and reaches about 7.5 at $\delta = 0.90$.

The effect of the green revenue premium on objective net payoff is more direct. After RM and MA-HE enter the high-adoption state, the average enterprise objective net payoff increases from about 3.36 to about 6.35 when v rises to 0.80. Under PT-MA, diffusion does not occur within the examined range of v, and the average objective net payoff remains close to 3.00. This result indicates that adoption alone is insufficient for evaluating green technology diffusion. Long-term diffusion requires technological cost reduction, stable quality, and market demand. Policy support is more suitable for helping enterprises cross the early adoption threshold.

4.4. Joint Effects of Technological Maturity and Loss Aversion

Figure 5 examines the joint effects of technological maturity and loss aversion. The parameter ranges are $\delta \in [0.10, 0.90]$ and $\lambda \in [1.00, 4.00]$. The respective step sizes are 0.05 and 0.25. All other parameters remain at their baseline values. PT-MA and MA-HE are compared. Figure 5a,b report steady-state adoption, and Figure 5c,d report the steady-state average enterprise net payoff. Each grid cell represents the terminal-window mean across independent simulation replications. Warmer colors indicate higher adoption or higher objective net payoff, while cooler colors indicate lower values.

Figure 5 indicates a pronounced interaction between technological maturity and loss aversion in PT-MA. Loss aversion increases the weight assigned to additional production costs and R&D risks. Greater technological maturity is therefore needed for green technology to gain an advantage in local rankings. When λ is close to 1.00, PT-MA enters the high-adoption region after δ reaches about 0.30–0.35. When λ increases to about 4.00, the diffusion threshold shifts to about $\delta = 0.75 - 0.80$. The sharp boundary indicates that local imitation can rapidly move the system from low to high adoption once perceived value crosses a critical level.

By contrast, the diffusion boundary in MA-HE is less sensitive to loss aversion. In Figure 5b, the high-adoption region is mainly determined by technological maturity. When δ exceeds about 0.30–0.35, the system generally enters the high-adoption state, and this boundary changes little with λ. The payoff panels show the same structure. Under PT-MA, the high-payoff region moves toward higher δ as λ increases. The payoff is about 3.00 in the low-maturity region and rises to about 7.5–8.0 after diffusion occurs at high maturity levels. Under MA-HE, the payoff mainly increases with technological maturity and reaches about 8.0 when δ approaches 0.90. These results indicate that improved enterprise appraisal can alleviate the influence of loss aversion, but it cannot substitute for technological progress and cost reduction.

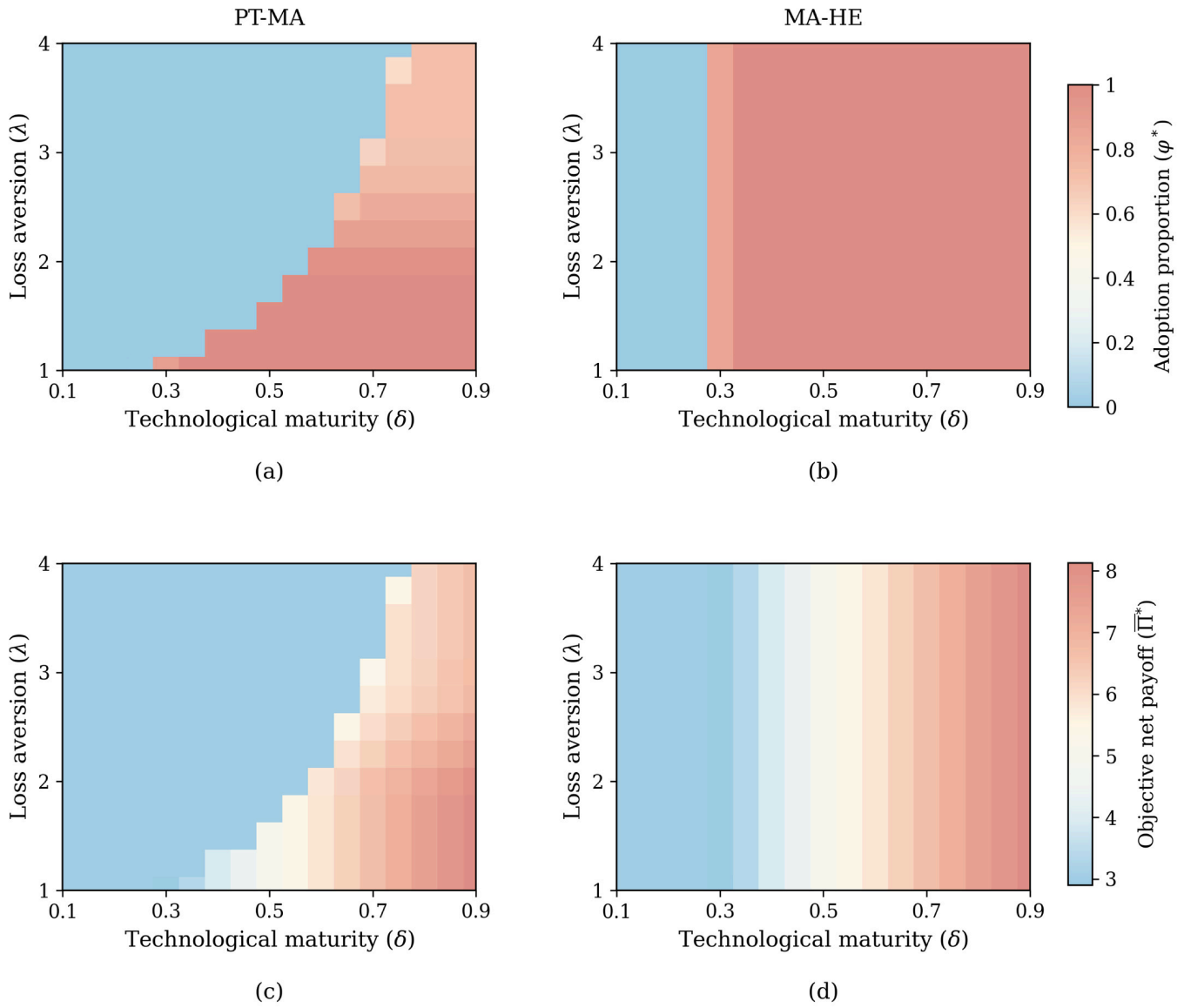


Figure 5. Joint effects of technological maturity and loss aversion: (**a**,**b**) steady-state adoption proportion under PT-MA and MA-HE, (**c**,**d**) objective net payoff under PT-MA and MA-HE. **Note:** The asterisk (*) indicates the steady-state value of this parameter.

4.5. Effects of Initial Adoption and Average Network Degree

The initial adoption proportion is varied over $\varphi_0 = 0.05, 0.10, \ldots, 0.65$, and average network degree takes the values $d \in \{2, 4, 6, 8, 10, 12\}$. Figure 6 compares PT-MA and MA-HE. Figure 6a,b present steady-state adoption, and Figure 6c,d present the steady-state average enterprise net payoff. Each grid cell represents the terminal-window mean across independent simulation replications. Warmer colors indicate higher adoption or higher objective net payoff.

Figure 6 shows a clear initial-adoption constraint under PT-MA. When there are too few early adopters, their local rankings are easily weakened by cost accounts and risk losses. Green technology may then be abandoned before reference points adjust. In Figure 6a, the terminal adoption proportion under PT-MA remains close to 0 in most regions when φ_0 is below about 0.60. Adoption increases locally only when φ_0 rises to about 0.65. Consistently, Figure 6c shows that the average enterprise objective net payoff remains close to 3.00 in most regions and increases slightly only under high initial adoption. This result indicates that green-technology diffusion requires a sufficiently large initial group to retain observable

and imitable local demonstrators. This finding is consistent with research showing that complex behavioral diffusion requires repeated exposure and social reinforcement [28].

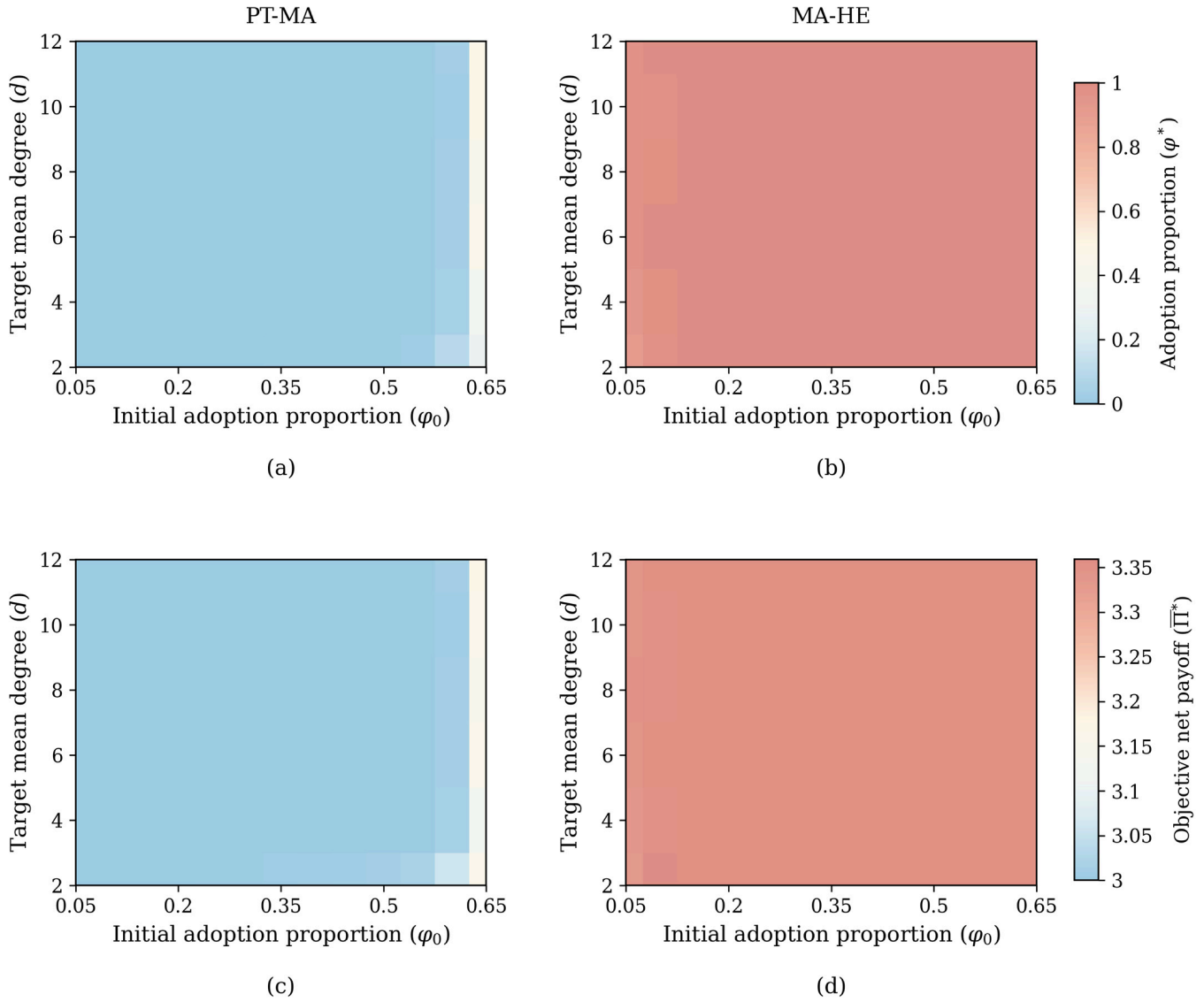


Figure 6. Joint effects of initial adoption and average network degree: (**a**,**b**) steady-state adoption proportion under PT-MA and MA-HE, (**c**,**d**) objective net payoff under PT-MA and MA-HE. **Note:** The asterisk (*) indicates the steady-state value of this parameter.

The effect of average network degree is conditional. More connections increase the visibility of advantageous strategies. However, they cannot compensate for an insufficient initial adopter group or inadequate perceived value. MA-HE maintains high adoption in the same parameter space. In Figure 6b, the terminal adoption proportion is generally close to 1, and Figure 6d shows that the average enterprise objective net payoff remains around 3.35. This further suggests that network connectivity mainly amplifies existing valuation advantages rather than creating them. Local fluctuations in the response surfaces arise from differences in BA network realizations and stochastic strategy updates during the early stages.

4.6. Joint Effects of Subsidies and Penalties

Figure 7 examines the joint effects of government subsidies and penalties on conventional technology in PT-MA and MA-HE. Subsidy intensity varies over $s \in [0, 4]$, and the penalty varies over $P \in [0, 3]$. Parameter combinations are evaluated using the specified

step sizes 0.25, while all other parameters remain at their baseline values. Figure 7a,b present steady-state adoption, and Figure 7c,d present the steady-state average enterprise net payoff. Similarly, each cell represents the terminal-window mean across independent replications, warmer colors indicate higher values.

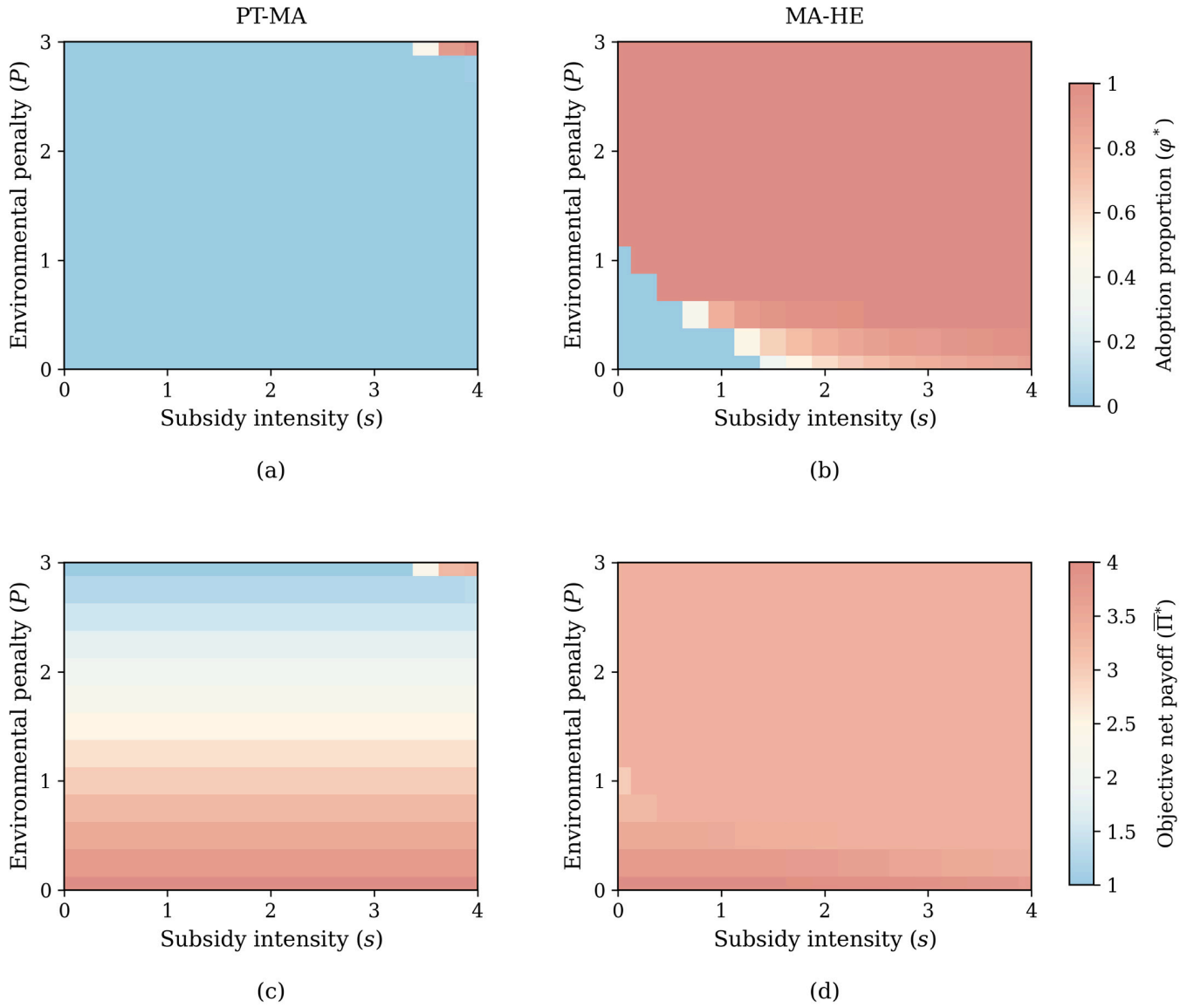


Figure 7. Joint effects of subsidies and penalties: (**a**,**b**) steady-state adoption proportion under PT-MA and MA-HE, (**c**,**d**) objective net payoff under PT-MA and MA-HE. **Note:** The asterisk (*) indicates the steady-state value of this parameter.

Figure 7 shows that subsidies and penalties are complementary, but PT-MA and MA-HE require substantially different policy intensities for high adoption. Subsidies increase the benefits of green technology. Penalties reduce the net payoff of conventional technology and raise its cost reference point. This narrows the relative cost disadvantage of green technology. Under PT-MA, adoption stays near zero in most policy combinations. High adoption appears only when both instruments are strong. For example, s is about 3.5–4.0 and P is about 3.0. This shows that separate account evaluation makes PT-MA more sensitive to the cost account and loss aversion. A strong policy mix is needed to cross the diffusion threshold.

MA-HE recognizes the overall advantage under weaker support. When P reaches about 1.0, high adoption can be maintained under most subsidy levels. When the penalty is low, s around 2.0–2.5 already promotes diffusion. The sharp boundaries come from account-based valuation, local rankings, and network imitation. They are not a simple linear marginal effect.

High adoption does not always mean high profit. Under PT-MA, if diffusion does not occur, stronger penalties mainly reduce net payoff. The payoff falls from about 3.5–4.0 in the low penalty region to about 1.0–1.5 in the high penalty region. Under MA-HE, net payoff is more stable, mostly around 3.0–3.6. Subsidies are withdrawn as adoption rises. Penalties reduce the attractiveness of conventional technology and encourage switching. But penalties do not directly improve green production efficiency. Subsidies are better for lowering early entry barriers. Penalties help internalize environmental costs. After subsidy withdrawal, sustained diffusion still depends on cost reduction and market returns. A single instrument is unlikely to achieve both technology diffusion and long-term economic performance [7,8,36].

5. Conclusions and Limitations

5.1. Conclusions

This study develops a green technology diffusion framework on a BA scale-free network. It compares RM, PT-MA, and MA-HE under identical payoff structures, network conditions, and strategy update rules. The analysis focuses on how valuation, outcome editing, and external conditions affect technology choices among CDW recycling enterprises. Three main conclusions follow.

(1) Account treatment changes diffusion outcomes under identical economic conditions. In the baseline simulation, RM and MA-HE both reach 100% steady-state adoption, whereas PT-MA reaches 0% steady-state adoption. This indicates that, even when green technology has an objective net payoff advantage, separate-account evaluation can amplify cost and risk losses and prevent green technology from spreading through neighborhood imitation. By contrast, MA-HE integrates benefits, costs, and risks, making adoption outcomes closer to objective payoff-based decisions. From a managerial perspective, enterprises should not evaluate green projects by highlighting isolated benefits or isolated costs. They should adopt a unified project appraisal framework that jointly considers product revenues, policy support, production expenditure, and R&D risks. Industry authorities should also improve cost–benefit disclosure and verification of demonstration projects to reduce uncertainty in enterprises' perceived returns from green technology.

(2) Green-technology diffusion has clear techno-economic thresholds, and these thresholds vary with the valuation rule. Around the baseline conditions, RM and MA-HE can form stable diffusion when technological maturity is about 0.35, whereas PT-MA requires technological maturity to increase to about 0.65 before adoption shifts markedly toward a high level. This suggests that hedonic editing can alleviate the barriers caused by loss aversion and separate-account evaluation, but it cannot replace actual technological progress. From a managerial perspective, enterprises and policymakers should treat technological maturity improvement, cost reduction, and risk control as the foundation of diffusion policy. Information presentation, project framing, and appraisal improvement can increase acceptance of green technology, but they need to be combined with quality certification, technology validation, and risk-sharing mechanisms to support sustained diffusion.

(3) Initial adoption, network connectivity, and policy instruments jointly shape diffusion thresholds, but high adoption does not necessarily imply high profitability. Under PT-

MA, green technology requires a sufficiently large early adopter base or a strong policy combination to cross the diffusion threshold, such as an initial adoption proportion of about 0.65, or subsidy intensity close to 3.5–4.0 combined with an environmental penalty close to 3.0. MA-HE diffuses under weaker policy conditions; for example, high adoption can be maintained under most subsidy levels once the environmental penalty reaches about 1.0. Meanwhile, environmental penalties mainly encourage switching by reducing the attractiveness of conventional technology, rather than directly improving green production efficiency. From a managerial perspective, governments should not evaluate policy effectiveness by adoption rates alone. Enterprise operating performance should also be considered. Early subsidies are suitable for lowering entry barriers, while environmental penalties help internalize the environmental costs of conventional technology. Long-term diffusion still depends on market demand, technological cost reduction, and stable product quality.

5.2. Limitations

This study has several limitations. The psychological parameters are primarily drawn from established studies and have not been calibrated using surveys of CDW recycling enterprises. The model does not fully capture heterogeneity in enterprise size, technological capabilities, or decision-making characteristics. Network relationships are also assumed to remain fixed. In addition, the government is represented only through external policy conditions. Fiscal budgets, environmental benefits, and social welfare are not explicitly modeled. Future research could estimate behavioral parameters using questionnaires, interviews, or behavioral experiments. It could also incorporate enterprise heterogeneity and endogenous network formation. Policy combinations could then be evaluated more comprehensively under environmental benefit considerations and fiscal constraints.

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Abbreviations

The following abbreviations are used in this manuscript:

CDW	Construction and Demolition Waste
R&D	Research and development
BA	Barabási–Albert
PT	Prospect theory
MA	Mental accounting
HE	Hedonic editing
RM	Rational benchmark model
PT-MA	Prospect theory–mental accounting model
MA-HE	Mental accounting–hedonic editing model

Appendix A

To examine whether the main model comparison depends on specific economic and policy parameter settings, a one-at-a-time sensitivity analysis is conducted. In each scenario, only one parameter is changed, while all other parameters remain at their baseline values. The examined parameters include the cost of conventional technology, the initial cost of green technology, R&D risk, green product revenue, subsidy intensity, and environmental penalty intensity. Adoption refers to the steady-state proportion of green-technology adopters, and objective net payoff refers to the steady-state average enterprise objective net payoff. All results are averages over 500 independent simulations. Each simulation contains 200 rounds, and steady-state outcomes are calculated from the average values of rounds 181–200.

Table A1 reports the steady-state adoption proportion and average objective net payoff of RM, PT-MA, and MA-HE under different parameter settings. The results show that the main comparison remains consistent under most parameter adjustments. When green technology retains a relative economic advantage, RM and MA-HE are more likely to generate high adoption, whereas PT-MA produces lower adoption. Changes in the initial cost of green technology and R&D risk have more visible effects on diffusion outcomes, indicating that cost reduction and risk control are important conditions for sustained green-technology diffusion. This sensitivity analysis provides supplementary support for the model comparison in the main text.

Table A1. Sensitivity analysis of adoption and objective net payoff under changes in economic and policy parameters.

Setting	RM Adoption (%)	PT-MA Adoption (%)	MA-HE Adoption (%)	RM Payoff	PT-MA Payoff	MA-HE Payoff
Baseline	100	0	100	3.36	3.00	3.36
$C_t = 4.8$	0.81	0	0	4.20	4.20	4.20
$C_t = 7.2$	100	0	100	3.36	1.80	3.36
$C_{g0} = 8$	100	0	100	4.77	3.00	4.77
$C_{g0} = 12$	0	0	0	3.00	3.00	3.00
$K_0 = 4.8$	100	0	100	4.20	3.00	4.20
$K_0 = 7.2$	52.72	0	52.93	2.99	3.00	2.99
$F_0 = 0.8$	100	0	100	3.43	3.00	3.43
$F_0 = 1.2$	100	0	100	3.28	3.00	3.28
$s = 1.2$	100	0	100	3.36	3.00	3.36
$s = 1.8$	100	0	100	3.36	3.00	3.36
$P = 0.8$	100	0	100	3.36	3.20	3.36
$P = 1.2$	100	0	100	3.36	2.80	3.36

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