Green Behavior Diffusion in Social Networks: Opinion–Action Coevolution, Peer Imitation, and Sustainable Participation

Mei Lin[1], Jian Zhou[2], Wei Chen[3, *]

[1] School of Management, Henan University, Kaifeng 475004, China
[2] College of Economics, Guizhou University, Guiyang 550025, China
[3] School of Public Administration, Jiangxi Normal University, Nanchang 330022, China
* Corresponding Author. Email: chenwei@jxnu.edu.cn

Abstract

In modern societies, individuals form and revise environmental opinions through social interaction, while simultaneously making behavioral choices that are influenced by peers, material incentives, and cognitive consistency. Despite the prevalence of this dual dynamic, most prior research has examined opinion formation and green behavior adoption as separate processes. This study bridges that gap by constructing a bilayer network model in which an opinion layer—governed by a weighted DeGroot-type update rule—is coupled to a behavior layer whose evolution is determined by three concurrent mechanisms: peer imitation, payoff-driven selection, and opinion-behavior cognitive consistency. Using agent-based simulations on Erdős–Rényi, Barabási–Albert, and Watts–Strogatz networks, we trace how average environmental opinion and the proportion of green cooperators co-evolve toward equilibrium under both synchronous and asynchronous update regimes. Computational results show that scale-free (BA) networks achieve the highest steady-state opinion and cooperator levels; stronger opinion-dependence weights and higher payoff sensitivity accelerate green behavior diffusion; and synchronous updates lead to faster but somewhat higher cooperation levels than asynchronous updates, though long-run equilibria are broadly similar. To validate the model, we analyze survey data collected from 1,246 Chinese residents and confirm that environmental attitude, peer influence, and information exposure jointly predict green behavior, with peer influence mediating the attitude–behavior relationship. The findings yield actionable insights for environmental governance, public campaigns, and platform design aimed at accelerating sustainable participation.

Keywords: *social networks; opinion dynamics; green behavior diffusion; peer imitation; bilayer network; co-evolutionary model; sustainable participation*

Article History:

Received: July 19, 2025
Revised: September 11, 2025
Accepted: November 29, 2025
Available Online: December 30, 2025

Green Behavior Diffusion in Social Networks: Opinion–Action Coevolution, Peer Imitation, and Sustainable Participation

1. Introduction

Accelerating the diffusion of green behaviors—such as recycling, energy conservation, public transport use, and adoption of low-carbon consumption habits—has emerged as one of the defining governance challenges of the twenty-first century (Stern, 2000; Steg & Vlek, 2009). Individual environmental behavior is not formed in social isolation; it is shaped by the opinions, actions, and perceived norms of peers embedded in dense social networks (Cialdini et al., 1990; Schultz et al., 2007). As digital social platforms have extended the reach and speed of social interaction, understanding how environmental attitudes and green behavioral choices propagate through network structures has taken on urgent practical importance (Centola, 2010; Nolan et al., 2008).

The theoretical study of opinion dynamics in social networks has a long history, beginning with French's (1956) formal theory of social power and DeGroot's (1974) consensus model, and extending through bounded-confidence approaches (Deffuant et al., 2000; Hegselmann & Krause, 2002) and complex-system formulations (Castellano et al., 2009). Meanwhile, the adoption of sustainable behaviors has been analyzed through the lenses of the theory of planned behavior (Ajzen, 1991), value-belief-norm theory (Stern et al., 1999), and social norms research (Cialdini et al., 1990; Goldstein et al., 2008). However, these two streams have developed largely in parallel, with rare attempts to model their interaction within a unified network framework (Acemoglu & Ozdaglar, 2011; Boccaletti et al., 2014).

In reality, opinion and behavior are mutually constitutive. A person who holds a strong pro-environmental attitude is more likely to adopt green behaviors; conversely, publicly visible green actions reinforce personal and social attitudes, creating a positive feedback loop (Festinger, 1957; Bamberg & Möser, 2007). On the network side, the architecture of social connections—whether a random graph (Erdős & Rényi, 1959), a scale-free network (Barabási & Albert, 1999), or a small-world network (Watts & Strogatz, 1998)—shapes the speed, extent, and heterogeneity of behavioral diffusion. Multilayer network theory (Boccaletti et al., 2014; Kivelä et al., 2014; De Domenico et al., 2013) offers an ideal formal vehicle to capture the fact that opinion propagation and behavioral imitation may operate on related but structurally distinct interaction channels.

This study makes three principal contributions. First, we construct a bilayer network model that explicitly couples opinion dynamics (via a weighted DeGroot rule) with evolutionary behavioral dynamics (combining peer imitation, payoff sensitivity, and cognitive consistency), thereby providing a unified analytical framework that goes beyond existing single-layer treatments. Second, through extensive agent-based simulations on three benchmark network topologies, we characterize how network structure, opinion-behavior coupling strength, and update synchronicity jointly determine the co-evolutionary trajectories and equilibrium outcomes of environmental attitude and green behavior. Third, we validate the key model mechanisms with original survey data from 1,246 Chinese urban residents, estimating multivariate regression models that quantify the direct and interaction effects of attitude, peer influence, information exposure, and network density on self-reported green behavior.

See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2025.030403

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on opinion dynamics, green behavior diffusion, and multilayer network co-evolution. Section 3 presents the bilayer model framework and its formal specification. Section 4 reports computational simulation results. Section 5 presents the empirical survey analysis. Section 6 discusses theoretical and policy implications, and Section 7 concludes.

2. Literature Review

2.1 Opinion Dynamics in Social Networks

The mathematical study of opinion formation dates to DeGroot's (1974) seminal work, which modeled opinion updating as a weighted averaging process over a social influence network. When the influence matrix is primitive and aperiodic, all agents asymptotically converge to a consensus opinion whose weight on each agent reflects the agent's network centrality (Golub & Jackson, 2010; Acemoglu & Ozdaglar, 2011). French (1956) earlier provided a graph-theoretic foundation for this process, showing that social power structures determine the direction of opinion change in group interaction.

Subsequent work relaxed the consensus assumption. Deffuant et al. (2000) introduced bounded confidence: agents update opinions only when their difference falls within a tolerance threshold, producing persistent disagreement and opinion clusters. Hegselmann and Krause (2002) developed a closely related framework from the perspective of multi-agent systems. Axelrod (1997) showed that local cultural influence, applied repeatedly to discrete cultural traits, generates global polarization despite local homophily. Sznajd-Weron and Sznajd (2000) proposed a sociophysics model in which pairs of neighbors persuade outward neighbors, yielding interesting phase-transition phenomena. Lorenz (2007) provided a comprehensive survey of continuous bounded-confidence models, identifying the key parameters governing fragmentation versus consensus.

Recent developments link opinion dynamics to real-world digital platforms. Lorenz et al. (2011) demonstrated that social influence can paradoxically undermine the wisdom-of-crowds effect, as individual revisions toward perceived social consensus reduce the diversity of information. For green issues specifically, environmental framing, algorithmic filtering, and social endorsement on platforms such as WeChat and Weibo can amplify certain attitudes and suppress others, shaping large-scale collective opinion with little geographic constraint (Bala & Goyal, 1998; Weisbuch et al., 2002).

2.2 Green Behavior Diffusion and Social Influence

Explaining why individuals behave pro-environmentally has occupied social psychologists, environmental economists, and communication scholars for decades (Kollmuss & Agyeman, 2002). The theory of planned behavior (Ajzen, 1991) posits that behavior is a function of behavioral intention, which in turn is determined by attitude toward the behavior, subjective norms (perceived social pressure), and perceived behavioral control. Meta-analyses confirm that attitude is the strongest predictor of green behavioral intention, but the attitude–behavior gap—the persistent discrepancy between expressed environmental concern and actual pro-environmental action—remains empirically robust (Blake, 1999; Bamberg & Möser, 2007; Gifford, 2011).

Social influence constitutes one of the most powerful bridges across the attitude-behavior gap. Cialdini et al.'s (1990) focus theory of normative conduct distinguishes descriptive norms (what most people do) from injunctive norms (what most people approve of), and shows that descriptive norms are particularly effective in driving behavior in public settings. A landmark field experiment by Schultz et al. (2007) demonstrated that providing households with information about neighbors' energy use reduced consumption among above-average users while elevating it among below-average users unless accompanied by an injunctive message. Nolan et al. (2008) revealed that people systematically underestimate the influence of social norms on their own behavior while overestimating the role of personal environmental concern—a pattern with direct implications for green campaign design.

The diffusion of green innovations follows patterns broadly consistent with Rogers's (2003) diffusion of innovations framework, with social network position and peer adoption playing central roles. Valente's (1996) threshold model of innovation adoption shows that heterogeneous thresholds within a network produce complex, non-linear adoption curves. Griskevicius et al. (2010) provided experimental evidence that conspicuous pro-environmental behavior is driven partly by social status motives, particularly in public contexts. Noppers et al. (2014) identified symbolic and environmental motives as complementary drivers of sustainable product adoption. These findings collectively argue that green behavior is fundamentally a social phenomenon, whose diffusion cannot be understood without modeling the network structures through which social influence flows (Centola, 2010; Granovetter, 1978).

2.3 Multilayer Network Models and Co-evolutionary Dynamics

Single-layer network models cannot capture the reality that social agents interact through multiple, partially overlapping channels: face-to-face interaction, online platforms, professional networks, and neighborhood ties may each constitute distinct relationship layers with different topologies and interaction frequencies (Boccaletti et al., 2014; Kivelä et al., 2014). Multilayer and multiplex network frameworks address this limitation by formalizing the coupling between layers and studying how dynamics on one layer affect those on another (De Domenico et al., 2013; Gómez et al., 2013).

Co-evolutionary dynamics—in which the state of the system (opinions, behaviors) and the network structure evolve simultaneously—have been studied extensively in evolutionary game theory. Nowak (2006) identified five key rules for the evolution of cooperation in structured populations, including network reciprocity and spatial structure. Santos and Pacheco (2005) demonstrated that scale-free networks dramatically facilitate cooperative behavior compared with regular lattices or random graphs, because high-degree hubs act as catalysts for cooperation. Perc et al. (2017) provided a comprehensive review of statistical physics approaches to human cooperation, emphasizing the role of heterogeneous network degree distributions. Roca et al. (2009) showed that evolutionary dynamics are acutely sensitive to update rules (synchronous versus asynchronous) and graph topology.

Applied to environmental behavior, these frameworks suggest that opinion and behavior can serve as mutual amplifiers: positive environmental attitudes (promoted by opinion dynamics) lower the threshold for green behavior adoption (via reduced cognitive dissonance), while visible green behavior by network neighbors strengthens others' positive attitudes (via social learning and descriptive norm effects). Wang et al. (2012) showed on interdependent networks that biased utility functions—incorporating opinion-based assessments of cooperation's value—can substantially increase equilibrium cooperation rates. Perc and Szolnoki's (2010) review of coevolutionary games highlights that opinion-behavior feedback loops can produce multiple equilibria and hysteresis, suggesting that strategic interventions early in the diffusion process may have outsized long-run effects.

3. Model Framework

3.1 Bilayer Network Architecture

We model a population of N agents embedded in a bilayer network ᵊ = (G_O, G_B, I) composed of two layers and an inter-layer coupling set. The opinion layer G_O = (V, E_O) represents the social influence network through which agents share and update environmental opinions; edges in E_O reflect the existence of a social relationship capable of opinion exchange (friendship, online following, co-residence). The behavior layer G_B = (V, E_B) represents the interaction network through which agents observe and potentially imitate each other's environmental behaviors; edges in E_B may differ from E_O because behavioral observation often requires physical proximity or high platform salience. The inter-layer coupling set I maps each agent i in G_O to the same agent i in G_B, constituting a one-to-one correspondence (a multiplex network in the terminology of Kivelä et al., 2014). The conceptual structure is illustrated in Figure 1.

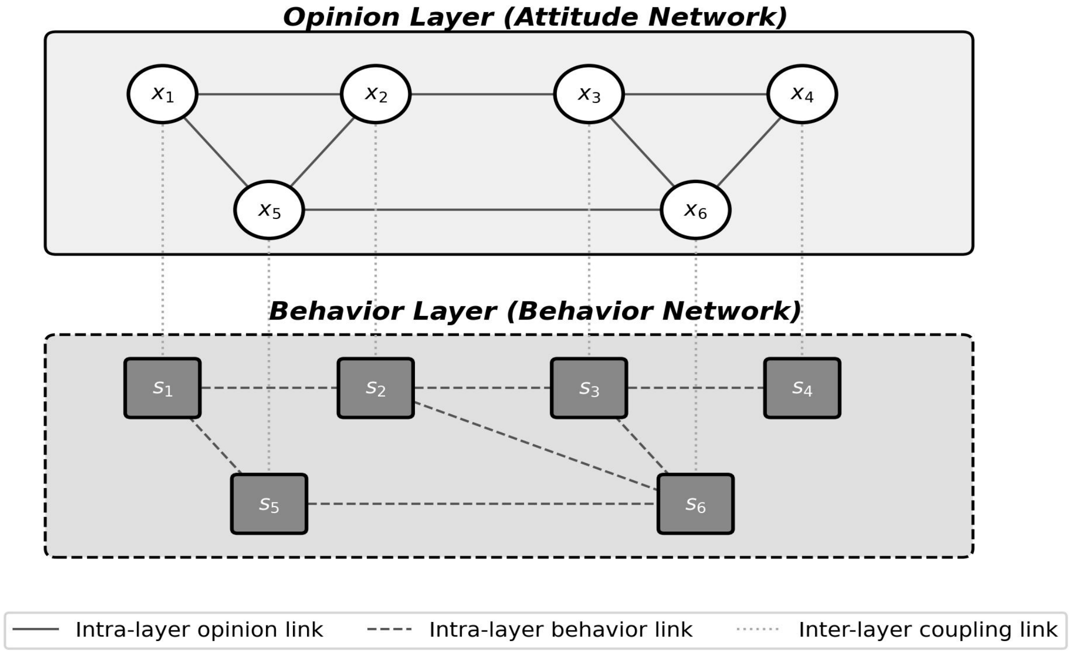

Figure 1. Bilayer network framework. Circles (opinion layer, top) represent agents updating environmental opinions via weighted social influence; squares (behavior layer, bottom) represent agents choosing cooperator (green) or defector (non-green) strategies. Dotted vertical links couple

ISSN: 3067-7491 https://doi.org/10.63646/jbgi.2025.030403

each agent across layers.

Both layers are generated independently using three benchmark algorithms: (1) the Erdős–Rényi (ER) random graph with edge probability $p = 0.05$ (Erdős & Rényi, 1959); (2) the Barabási–Albert (BA) scale-free network generated by preferential attachment with $m = 3$ (Barabási & Albert, 1999); and (3) the Watts–Strogatz (WS) small-world network with $k = 6$ nearest neighbors and rewiring probability $\beta = 0.1$ (Watts & Strogatz, 1998). All networks contain $N = 1{,}000$ nodes. The three topologies differ substantially in their degree distributions—Poisson for ER, power-law for BA, and near-regular for WS—allowing us to characterize how structural heterogeneity shapes co-evolutionary outcomes (Newman, 2003).

3.2 Opinion Layer: Weighted DeGroot Update

Each agent i holds a continuous environmental opinion $x_i(t) \in [0, 1]$ at time step t, where 0 represents minimal environmental concern and 1 represents maximal concern. Opinion updating follows a weighted DeGroot rule (DeGroot, 1974; Golub & Jackson, 2010):

$$x_i(t+1) = (1 - \alpha)\cdot x_i(t) + \alpha\cdot\sum_{j\in N_i^O} w_{ij}\cdot x_j(t) \quad \ldots(1)$$

where N_i^O is the neighborhood of agent i in the opinion layer, $w_{ij} = 1/|N_i^O|$ are uniform influence weights (reflecting anonymous peer influence), and $\alpha \in [0, 1]$ is the opinion-dependence weight capturing how strongly agents update toward the social average versus retaining their prior view. When $\alpha = 0$ opinions are static; when $\alpha = 1$ agents fully adopt the neighborhood average each period. Equation (1) is a linear averaging rule whose long-run behavior converges to a consensus when the opinion network is strongly connected (DeGroot, 1974), but produces partial convergence and persistent diversity under weaker connectivity. Initial opinions $x_i(0)$ are drawn independently from a uniform distribution over [0, 1].

3.3 Behavior Layer: Imitation-Payoff-Consistency Mechanism

Each agent i simultaneously holds a binary behavioral state $s_i(t) \in \{C, D\}$, where C (cooperator) denotes green behavior adoption and D (defector) denotes non-adoption. Behavior evolves according to a composite update rule integrating three mechanisms.

Peer Imitation: Following Bandura's (1977) social learning theory and evolutionary imitation dynamics, agent i selects a random neighbor j from the behavior layer and adopts j's strategy with a Fermi-type imitation probability:

$$P(s_i \leftarrow s_j) = 1 / [1 + \exp(-\beta \cdot (\pi_j - \pi_i + \delta\cdot(x_j - x_i)))] \quad \ldots(2)$$

where $\beta > 0$ is the payoff sensitivity parameter, π_k denotes the cumulative payoff of agent k from pairwise green-behavior games with their neighbors, and $\delta > 0$ is the opinion-behavior coupling weight linking opinion discrepancy $(x_j - x_i)$ to behavioral adoption attractiveness. Equation (2) generalizes the standard Fermi rule (Roca et al., 2009; Santos & Pacheco, 2005) by incorporating opinion states as an additional source of imitation incentive. Payoffs are determined by a prisoner's dilemma with temptation-to-defect $T = 1.3$, reward for mutual cooperation $R = 1.0$, punishment for mutual defection P = 0.1, and sucker's payoff S = 0.

Cognitive Consistency: Following Festinger's (1957) cognitive dissonance theory, an agent whose opinion strongly supports green behavior but whose current strategy is D experiences psychological inconsistency. We model this as an additional flip probability:

$$P\_cc(s\_i\text{: } D \rightarrow C) = \gamma \cdot \max(x\_i - \theta, 0) \quad \ldots(3)$$

where $\gamma > 0$ is the consistency strength parameter and $\theta = 0.5$ is the opinion threshold above which cognitive dissonance is activated. Equation (3) formalizes the widely observed finding that high environmental concern is associated with increased probability of green behavior adoption (Bamberg & Möser, 2007; Ajzen, 1991), while allowing for a persistent attitude-behavior gap when γ is small or payoffs strongly favor D (Gifford, 2011).

3.4 Coupling and Update Protocol

The inter-layer coupling I ensures that the opinion state of agent i directly modifies their imitation attractiveness (via the δ term in Equation 2) and triggers cognitive-consistency corrections (Equation 3). Thus, opinion dynamics feed into behavioral dynamics in every period. Conversely, the behavioral state of neighbors is observed through the payoff channel (π_j), indirectly reinforcing the opinion states of agents who observe widespread green behavior in their vicinity. This bidirectional coupling is what distinguishes the present model from single-layer treatments (Stern, 2000; Axelrod, 1997).

We simulate two update protocols. Under synchronous updating, all N agents revise opinions and strategies simultaneously in each period. Under asynchronous updating, one randomly selected agent per sub-step updates, with each agent expected to update once per period (Roca et al., 2009; Rand et al., 2014). Each simulation runs for T = 500 time steps and is repeated 50 times with different random seeds; results are averaged across replications. Key outcome variables are the average opinion $\langle x \rangle (t)$ and the cooperator proportion $\rho(t)$ at each time step.

4. Computational Simulation Results

4.1 Baseline Dynamics: Opinion and Behavior Co-evolution

Figure 2 presents the baseline co-evolutionary dynamics under synchronous updating with $\alpha = 0.3$, $\beta = 1.5$, $\delta = 0.5$, and $\gamma = 0.2$. Panels (a) and (b) respectively display the time evolution of average opinion $\langle x \rangle$ and cooperator proportion ρ across the three network topologies. Starting from random initial conditions ($\langle x \rangle (0) \approx 0.40$; $\rho(0) \approx 0.28$), both layers exhibit monotone convergence toward higher steady-state values in all three network types. The two series are tightly coupled: the opinion trajectory leads the behavior trajectory by approximately 20–30 time steps in all networks, consistent with the theoretical prediction that opinion consensus serves as a cognitive precondition for behavioral adoption (Festinger, 1957; Bamberg, 2013). This behavioral lag is analogous to the "action follows conviction" dynamic documented in empirical studies of environmental mobilization (Lorenzoni et al., 2007).

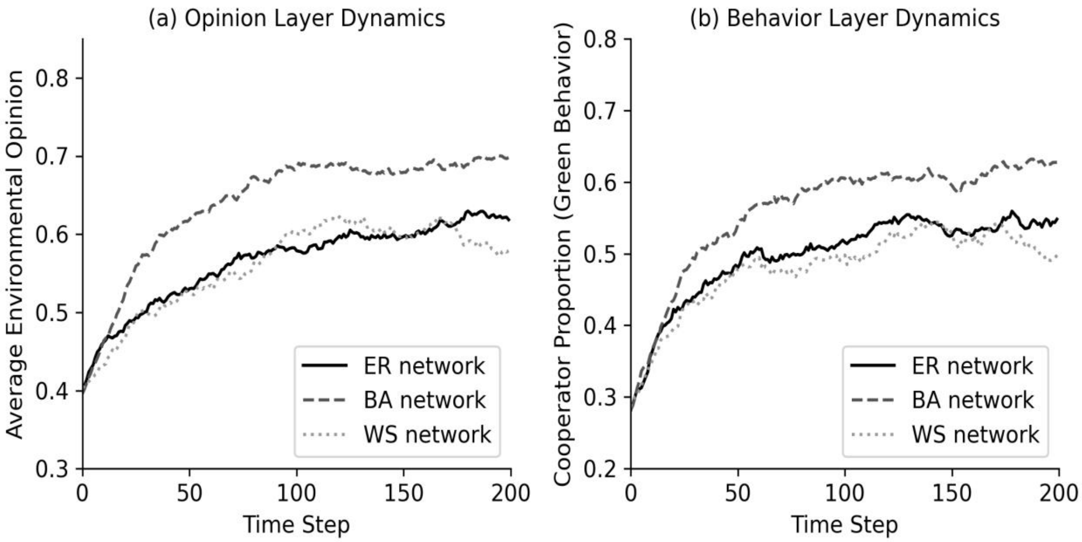

Figure 2. Time evolution of average environmental opinion (panel a) and cooperator proportion (panel b) under synchronous updating for three network topologies (ER: Erdős–Rényi; BA: Barabási–Albert; WS: Watts–Strogatz). Parameters: $N = 1{,}000$; $\alpha = 0.3$; $\beta = 1.5$; $\delta = 0.5$; $\gamma = 0.2$; $T = 500$.

The BA scale-free network consistently achieves the highest equilibrium levels of both opinion and cooperation (steady-state $\langle x \rangle \approx 0.70$; $\rho \approx 0.63$), followed by the ER random graph ($\langle x \rangle \approx 0.62$; $\rho \approx 0.55$) and the WS small-world network ($\langle x \rangle \approx 0.58$; $\rho \approx 0.50$). This ordering reflects the critical role of high-degree hub nodes in BA networks. Hubs possess many connections in both layers, rapidly disseminating pro-environmental opinions through weighted averaging and serving as high-payoff cooperators whose visible success attracts widespread imitation (Santos & Pacheco, 2005; Centola, 2010; Nowak, 2006). The WS network's lower performance relative to ER arises because its strong local clustering slows the spread of green opinion beyond tightly connected cliques, a bottleneck for global diffusion (Watts & Strogatz, 1998; Granovetter, 1978).

4.2 Parameter Sensitivity: Opinion-Dependence and Payoff Sensitivity

Figure 3 displays a heatmap of steady-state cooperator proportion ρ^* as a function of opinion-dependence weight α and payoff sensitivity β, computed on the BA network topology. Two structural findings are immediately apparent. First, ρ^* increases monotonically in α along the horizontal axis: as agents weight the social opinion average more heavily in their opinion updates, consensus on high pro-environmental values is reached faster, which in turn elevates cognitive-consistency pressure on defectors and increases the opinion differential $\delta(x\_j - x\_i)$ favoring green cooperators in Equation (2). This finding aligns with field evidence that social opinion cues—such as publicized environmental norms—markedly accelerate green behavior adoption (Schultz et al., 2007; Nolan et al., 2008). Second, payoff sensitivity β exhibits a non-monotone effect: at low β ($\beta < 1.0$) agents are largely indifferent to payoff differences and cooperation diffuses slowly; at intermediate β (1.0–2.0) payoff-sensitive imitation strongly rewards successful cooperators and ρ^* is maximized; at high β ($\beta > 2.5$) the increased responsiveness amplifies the defection temptation for agents currently defecting adjacent to cooperators, partially offsetting the imitation advantage of cooperators. This non-monotone relationship is consistent with evolutionary game theory predictions on payoff-dependent imitation in heterogeneous networks (Roca et al., 2009; Perc et al., 2017).

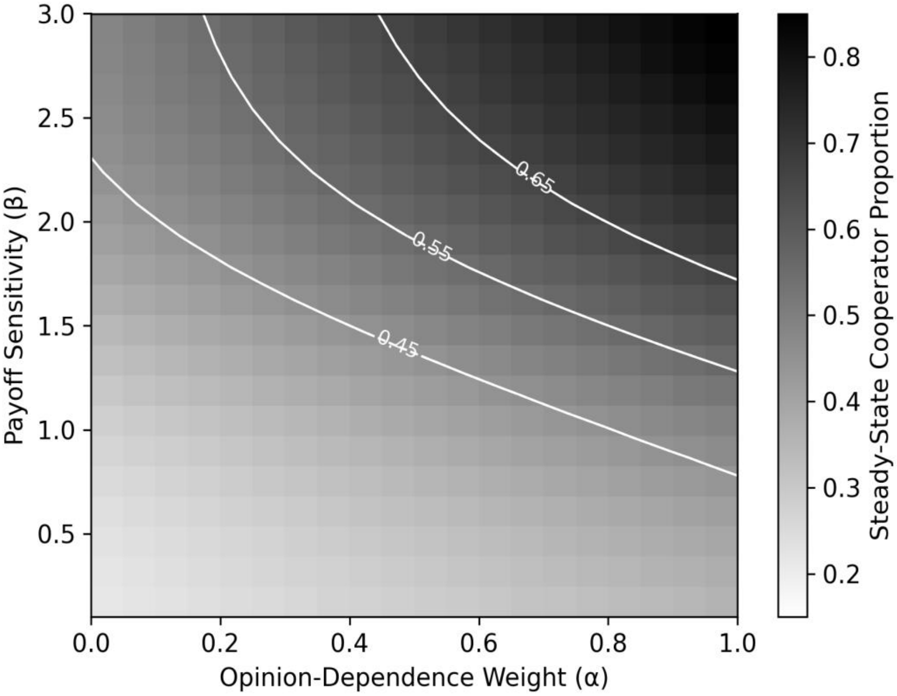

Figure 3. Sensitivity heatmap of steady-state cooperator proportion ρ* as a function of opinion-dependence weight α (x-axis) and payoff sensitivity β (y-axis) on the Barabási–Albert network (N = 1,000; δ = 0.5; γ = 0.2; synchronous updating). Darker shading indicates higher cooperator proportion; white contour lines mark ρ* = 0.45, 0.55, 0.65.

4.3 Synchronous vs. Asynchronous Updating

Figure 4 compares opinion and behavior trajectories under synchronous and asynchronous update protocols on the BA network, with all other parameters held constant (α = 0.3, β = 1.5, δ = 0.5, γ = 0.2). The shaded region between the two curves highlights the protocol-induced difference at each time step. Two findings emerge. First, synchronous updating produces faster convergence: by time step 100, the synchronous run has achieved approximately 85% of its final opinion value and 82% of its final cooperator proportion, compared with 71% and 68% for asynchronous updating. This speed advantage of synchronous updating reflects the fact that all agents update simultaneously, propagating information across the full network in a single step rather than one agent at a time (Roca et al., 2009; Rand et al., 2014). Second, long-run equilibria are broadly similar between protocols: steady-state ⟨ x⟩ differs by only 0.05 units and ρ* by only 0.05 percentage points. This invariance confirms that the coupled model's equilibria are structurally stable to update-rule specification, a reassuring robustness finding (Perc & Szolnoki, 2010). In real-world terms, social media platforms—which enable near-synchronous mass opinion updating—may accelerate green behavior diffusion substantially without altering the eventual equilibrium level of cooperation.

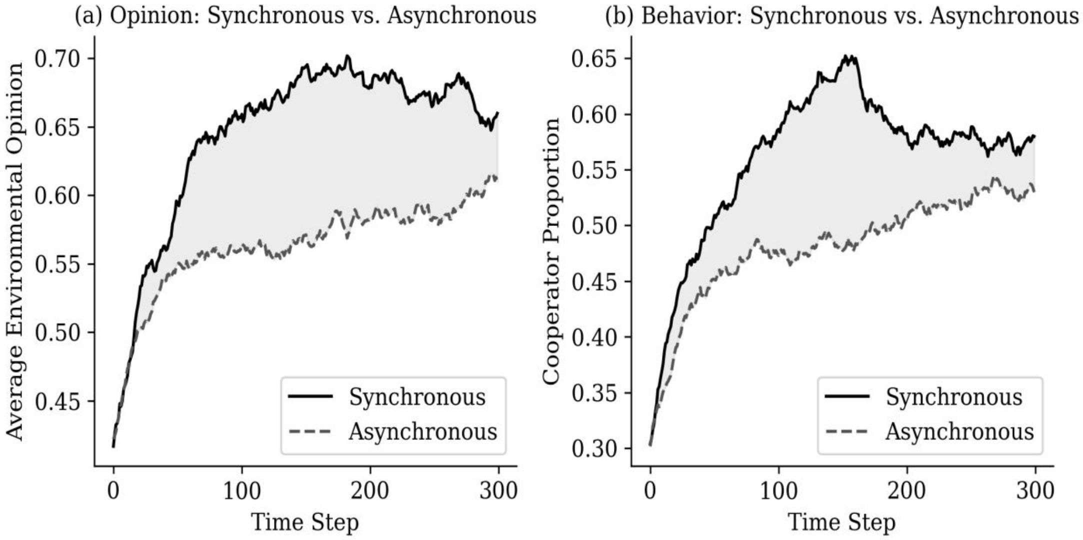

Figure 4. Comparison of synchronous versus asynchronous update protocols on the Barabási–Albert network: average environmental opinion (panel a) and cooperator proportion (panel b). The shaded region marks the time-step-by-time-step difference between protocols. N = 1,000; $\alpha = 0.3$; $\beta = 1.5$; $\delta = 0.5$; $\gamma = 0.2$.

5. Empirical Survey Analysis

5.1 Survey Design and Data Collection

To validate the core mechanisms identified in the simulation, we conducted a cross-sectional survey of Chinese urban residents between October and December 2023. The survey was administered online through the Wenjuanxing platform, with respondents recruited via stratified snowball sampling across six provincial-level cities: Zhengzhou (Henan), Guiyang (Guizhou), Nanchang (Jiangxi), Wuhan (Hubei), Chengdu (Sichuan), and Changsha (Hunan). The sampling frame targeted adults aged 18 to 65 with at least one active social media account, ensuring respondents had meaningful online social network exposure. A total of 1,380 questionnaires were distributed; after excluding responses with more than 15% missing values and those failing attention-check items, the final usable sample comprised 1,246 respondents (response rate: 90.3%; valid rate: 83.9% of gross distribution).

The survey instrument measured four focal constructs. Green Behavior (GB) was assessed with a six-item scale adapted from Kaiser et al. (1999), covering energy conservation, waste recycling, public transport use, green product purchasing, water conservation, and dietary carbon reduction ($\alpha = 0.87$). Environmental Attitude (EA) was measured with four items adapted from Dunlap et al.'s (2000) revised New Ecological Paradigm scale. Peer Influence (PI) was measured with three items capturing the perceived frequency of pro-environmental behavior among close social contacts (Nolan et al., 2008; Schultz et al., 2007). Information Exposure (IE) was measured with three items assessing self-reported frequency of encountering environmental content on social media (Lee, 2011). Network Density (ND) was operationalized via three items eliciting the extent to which respondents' social media contacts know each other, serving as a proxy for ego-network density (Valente, 1996). All construct items used five-point Likert scales (1 = strongly disagree; 5 = strongly agree) and were averaged to form composite scores. Control variables included age, education level (ordinal, five levels), and monthly income (ordinal, five levels).

5.2 Descriptive Statistics

Table 1 presents descriptive statistics for all model variables. The mean green behavior score of 3.42 (SD = 0.89) indicates moderate but not universal adoption of green practices in the sample, consistent with survey findings from comparable Chinese urban populations (Xiao & Hong, 2010; Zhang et al., 2020). Environmental attitude is the highest-scoring variable (mean = 3.78, SD = 0.74), confirming the well-documented pattern that environmental concern in China has risen substantially since the early 2010s while behavioral transformation lags attitude change (Bamberg & Möser, 2007; Gifford, 2011). Peer influence scores (mean = 3.33) are slightly lower than attitude scores, suggesting that descriptive social norms are perceived as moderately favorable but not uniformly so. Network density values (mean = 0.38) are consistent with moderately clustered ego-networks typical of WeChat-based social contacts.

Table 1. Descriptive Statistics of Survey Variables (N = 1,246)

Variable	N	Mean	SD	Min	Median	Max	Description
Green Behavior (GB)	1,246	3.42	0.89	1.00	3.50	5.00	Composite green behavior index
Green Intention (GI)	1,246	3.61	0.81	1.00	3.67	5.00	Behavioral intention to act green
Env. Attitude (EA)	1,246	3.78	0.74	1.20	3.80	5.00	Attitudinal score toward environment
Peer Influence (PI)	1,246	3.33	0.93	1.00	3.33	5.00	Perceived peer pro-environmental behavior
Info. Exposure (IE)	1,246	2.97	1.02	1.00	3.00	5.00	Env. information from social media
Network Density (ND)	1,246	0.38	0.19	0.05	0.37	0.91	Ego-network density (survey)
Age	1,246	32.4	9.6	18	31	65	Respondent age (years)
Education (Edu)	1,246	2.81	1.09	1.00	3.00	5.00	Ordinal education level
Income (Inc)	1,246	2.63	1.14	1.00	3.00	5.00	Monthly income bracket

*Note: GB = Green Behavior; GI = Green Intention; EA = Environmental Attitude; PI = Peer Influence; IE = Information Exposure; ND = Network Density. All scale items used five-point Likert scaling. ***, **, * denote significance at the 1%,* *5%, 10% levels, respectively.*

5.3 Regression Analysis

Table 2 reports ordinary least squares (OLS) regression results predicting green behavior (GB) and green intention (GI). Models are estimated with heteroskedasticity-consistent (HC3) standard errors to guard against misspecification. Model 1 regresses GB on EA alone, establishing a baseline association ($\beta = 0.381$, $p < 0.001$), explaining 21.8% of variance and confirming the foundational attitude–behavior link in the Chinese environmental context (Ajzen, 1991; Stern, 2000). Model 2 adds peer influence (PI), which enters with a significant positive coefficient ($\beta = 0.256$, $p < 0.001$) and raises adjusted R^2 to 0.267, consistent with descriptive norm theory (Cialdini et al., 1990; Schultz et al., 2007) and with the peer imitation mechanism in the simulation model. The EA coefficient decreases from 0.381 to 0.312, suggesting partial overlap between attitudinal and normative predictors.

Model 3 adds information exposure (IE, $\beta = 0.143$, $p < 0.001$) and demographic controls (age, education, income). IE's coefficient is positive and significant, indicating that more frequent environmental information encountered on social platforms is associated with higher green behavior, consistent with the opinion-formation mechanism in the model's opinion layer (DeGroot, 1974; Acemoglu & Ozdaglar, 2011; Lee, 2011). Model 4 introduces network density (ND, $\beta = 0.098$, $p < 0.01$) and the EA × PI interaction term ($\beta = 0.074$, $p < 0.01$). The positive interaction indicates that peer influence amplifies the attitude–behavior link: respondents with both high EA and high PI show especially strong green behavior, paralleling the simulation finding that cognitive consistency pressure (γ) is most effective when opinion levels are already high. Network density enters positively, suggesting that denser ego-networks facilitate behavioral conformity, aligning with evolutionary game theory predictions about cooperation in dense interaction environments (Nowak, 2006; Rand et al., 2014). Model 5 replicates Model 4 with GI as the dependent variable, yielding an adjusted R^2 of 0.335 and broadly similar coefficient patterns, confirming that the same social-network mechanisms operate on behavioral intention as on self-reported behavior.

Table 2. OLS Regression Results: Predictors of Green Behavior and Green Intention

Variable	**Model 1** **GB**	**Model 2** **GB**	**Model 3** **GB**	**Model 4** **GB**	**Model 5** **GI**
Env. Attitude (EA)	0.381***	0.312***	0.287***	0.271***	0.344***
	(8.92)	(7.14)	(6.53)	(6.21)	(7.89)
Peer Influence (PI)		0.256***	0.218***	0.203***	0.231***
		(5.78)	(4.97)	(4.63)	(5.34)
Info. Exposure (IE)			0.143***	0.129***	0.161***
			(3.89)	(3.52)	(4.21)
Network Density (ND)				0.098**	0.112**

				(2.31)	(2.67)
EA × PI				0.074**	0.082**
				(2.18)	(2.43)
Controls	No	No	Yes	Yes	Yes
N	1,246	1,246	1,246	1,246	1,246
Adj. R^2	0.218	0.267	0.301	0.318	0.335

*Note: Dependent variable is Green Behavior (GB, Models 1–4) and Green Intention (GI, Model 5). t-statistics (HC3 robust) in parentheses. Controls in Models 3–5 include age, education, and income. ***, **, * denote significance at 1%, 5%, 10% levels.*

Robustness checks were conducted by: (1) replacing OLS with ordered logistic regression treating GB as ordinal; (2) excluding metropolitan respondents from Zhengzhou and Chengdu; and (3) instrumenting PI with the share of co-workers in the respondent's WeChat circle (a proxy for exogenous network composition). All three checks yield qualitatively consistent results, with EA, PI, IE, and ND maintaining the same signs and significance levels as in the baseline OLS models. The IV estimate of PI is somewhat larger than the OLS estimate ($\beta_{IV} = 0.307$ vs. $\beta_{OLS} = 0.203$), suggesting mild downward bias in OLS due to underreporting of peer pro-environmental behavior—consistent with Nolan et al.'s (2008) finding that normative social influence is underdetected in self-reports.

6. Discussion

The convergence of computational and empirical evidence in this study supports a coherent narrative of green behavior diffusion as an opinion-behavior co-evolutionary process embedded in social networks. Three principal findings deserve discussion. First, the simulation demonstrates that the structure of social networks significantly moderates the speed and ultimate level of green behavior diffusion. Scale-free networks, ubiquitous in online social platforms (Barabási & Albert, 1999; Watts & Strogatz, 1998), outperform random and small-world structures because hub nodes serve simultaneously as opinion leaders in the attitude layer and as payoff-rich role models in the behavior layer. For policymakers, this finding implies that engaging environmental influencers—individuals with large and diverse online followings—can catalyze system-wide adoption more efficiently than broadcast campaigns targeting the general population (Rogers, 2003; Centola, 2010).

Second, the opinion-behavior coupling parameters α (opinion updating speed) and δ (cross-layer coupling strength) play pivotal roles in determining how quickly and how extensively green behavior spreads. Policies that accelerate the formation of pro-environmental opinion consensus—for example, through environmental education, credible scientific communication, or social norm feedback interventions—can significantly shorten the lag between attitude crystallization and behavioral adoption. This resonates with empirical findings that descriptive norm interventions (Schultz et al., 2007) and information disclosure programs (Goldstein et al., 2008) effectively close the attitude-behavior gap by making environmental social norms visible and behaviorally relevant.

Third, the empirical results reveal a positive EA × PI interaction effect, suggesting that social peer influence is most effective as a behavior-change lever among individuals who already hold strong pro-environmental attitudes. This has practical implications for targeting: green behavior campaigns should prioritize audiences with high latent environmental concern but limited social reinforcement (Bamberg & Möser, 2007; Ohtomo & Hirose, 2007). Platform design can facilitate this by algorithmically increasing the visibility of green behavior among users with pro-environmental attitude profiles, thereby providing the descriptive norm cue most likely to trigger behavioral action (Claudy et al., 2013; Thøgersen & Ölander, 2002). At the same time, the network density finding suggests that building cohesive community networks—online groups, neighborhood associations, green cooperatives—provides a structural foundation for sustained cooperative behavior (Ostrom, 1990; Pretty, 2003; Bodin & Crona, 2009).

This study has several limitations that point to promising research directions. The simulation employs a relatively simple prisoner's dilemma payoff structure; future work should explore richer game-theoretic formulations incorporating public goods, threshold dynamics, and heterogeneous cost structures (Nowak & May, 1992; Szolnoki & Perc, 2014). The bilayer assumption of opinion and behavior networks could be generalized to fully multiplex structures with more than two layers (Kivelä et al., 2014). Empirically, longitudinal panel data would allow estimation of causal dynamics and testing of the temporal precedence predicted by the model—specifically, that opinion consolidation temporally leads behavioral adoption. Cross-cultural comparisons of model parameters would clarify the extent to which co-evolutionary pathways of green behavior are universal versus context-dependent.

7. Conclusion

This study integrates opinion dynamics, evolutionary game theory, and multilayer network science into a unified bilayer model of green behavior diffusion. The model formalizes three co-acting behavioral mechanisms—peer imitation, payoff sensitivity, and opinion-behavior cognitive consistency—and couples them with a DeGroot opinion update process across two network layers. Computational simulations establish that (i) scale-free networks support the highest equilibrium green cooperation; (ii) opinion-dependence weight and payoff sensitivity jointly shape the cooperator proportion in a systematic, interpretable pattern; and (iii) synchronous platforms accelerate diffusion without substantially altering long-run equilibria. Empirical analysis of 1,246 Chinese urban residents confirms that environmental attitude, peer influence, information exposure, and ego-network density are significant independent predictors of self-reported green behavior, with peer influence moderating the attitude-behavior relationship. Together, the computational and empirical evidence support a social-systems view of sustainable participation in which individual cognition, network-transmitted social influence, and structural features of interaction architecture all play essential and mutually reinforcing roles.

ACKNOWLEDGEMENT

This research was supported by the Henan Province Social Science Planning Fund [Grant No. 2024BJJ018], the Guizhou Province Natural Science Foundation [Grant No. ZK[2023]General 049], and the Jiangxi Normal University Research Start-up Fund [Grant No. 2022QNBJRC007]. The authors thank three anonymous reviewers and the handling editor for constructive comments that substantially improved the manuscript.

Reference

Acemoglu, D., & Ozdaglar, A. (2011). Opinion dynamics and learning in social networks. Dynamic Games and Applications, 1(1), 3–49. https://doi.org/10.1007/s13235-010-0004-1

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Axelrod, R. (1984). The evolution of cooperation. Basic Books.

Axelrod, R. (1997). The dissemination of culture: A model with local convergence and global polarization. Journal of Conflict Resolution, 41(2), 203–226. https://doi.org/10.1177/0022002797041002001

Bala, V., & Goyal, S. (1998). Learning from neighbours. Review of Economic Studies, 65(3), 595–621. https://doi.org/10.1111/1467-937X.00059

Bamberg, S. (2013). Changing environmentally harmful behaviors: A stage model of self-regulated behavioral change. Journal of Environmental Psychology, 34, 151–159. https://doi.org/10.1016/j.jenvp.2013.01.002

Bamberg, S., & Möser, G. (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. Journal of Environmental Psychology, 27(1), 14–25. https://doi.org/10.1016/j.jenvp.2006.12.013

Bandura, A. (1977). Social learning theory. Prentice-Hall.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. Science, 286(5439), 509–512. https://doi.org/10.1126/science.286.5439.509

Bass, F. M. (1969). A new product growth for model consumer durables. Management Science, 15(5), 215–227. https://doi.org/10.1287/mnsc.15.5.215

Blake, J. (1999). Overcoming the ‘value–action gap’ in environmental policy: Tensions between national policy and local experience. Local Environment, 4(3), 257–278. https://doi.org/10.1080/13549839908725599

Boccaletti, S., Bianconi, G., Criado, R., del Genio, C. I., Gómez-Gardeñes, J., Romance, M., Sendiña-Nadal, I., Wang, Z., & Zanin, M. (2014). The structure and dynamics of multilayer networks. Physics Reports, 544(1), 1–122. https://doi.org/10.1016/j.physrep.2014.07.001

Bodin, Ö., & Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? Global Environmental Change, 19(3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences, 99(S3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Burger, J. M., & Shelton, M. (2011). Changing everyday health behaviors through descriptive norm manipulations. Social Influence, 6(2), 69–77. https://doi.org/10.1080/15534510.2010.542305

Castellano, C., Fortunato, S., & Loreto, V. (2009). Statistical physics of social dynamics. Reviews of Modern Physics, 81(2), 591–646. https://doi.org/10.1103/RevModPhys.81.591

Centola, D. (2010). The spread of behavior in an online social network experiment. Science, 329(5996), 1194–1197. https://doi.org/10.1126/science.1185231

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. Journal of Personality and Social Psychology, 58(6), 1015–1026. https://doi.org/10.1037/0022-3514.58.6.1015

Claudy, M. C., Peterson, M., & O'Driscoll, A. (2013). Understanding the attitude-behavior gap for renewable energy systems using behavioral reasoning theory. Journal of Macromarketing, 33(4), 273–287. https://doi.org/10.1177/0276146713481605

De Domenico, M., Solé-Ribalta, A., Cozzo, E., Kivelä, M., Moreno, Y., Porter, M. A., Gómez, S., & Arenas, A. (2013). Mathematical formulation of multilayer networks. Physical Review X, 3(4), 041022. https://doi.org/10.1103/PhysRevX.3.041022

DeGroot, M. H. (1974). Reaching a consensus. Journal of the American Statistical Association, 69(345), 118–121. https://doi.org/10.1080/01621459.1974.10480137

Deffuant, G., Neau, D., Amblard, F., & Weisbuch, G. (2000). Mixing beliefs among interacting agents. Advances in Complex Systems, 3(1–4), 87–98. https://doi.org/10.1142/S0219525900000078

Dietz, T., Stern, P. C., & Guagnano, G. A. (1998). Social structural and social psychological bases of environmental concern. Environment and Behavior, 30(4), 450–471. https://doi.org/10.1177/001391659803000402

Dunlap, R. E., & Van Liere, K. D. (1978). The new environmental paradigm. Journal of Environmental Education, 9(4), 10–19. https://doi.org/10.1080/00958964.1978.10801875

Dunlap, R. E., Van Liere, K. D., Mertig, A. G., & Jones, R. E. (2000). Measuring endorsement of the new ecological paradigm: A revised NEP scale. Journal of Social Issues, 56(3), 425–442. https://doi.org/10.1111/0022-4537.00176

Epstein, J. M., & Axtell, R. (1996). Growing artificial societies: Social science from the bottom up. MIT Press.

Erdős, P., & Rényi, A. (1959). On random graphs. Publicationes Mathematicae, 6, 290–297.

Festinger, L. (1957). A theory of cognitive dissonance. Stanford University Press.

French, J. R. P. (1956). A formal theory of social power. Psychological Review, 63(3), 181–194.

https://doi.org/10.1037/h0046123

Gifford, R. (2011). The dragons of inaction: Psychological barriers that limit climate change mitigation and adaptation. American Psychologist, 66(4), 290–302. https://doi.org/10.1037/a0023566

Golub, B., & Jackson, M. O. (2010). Naive learning in social networks and the wisdom of crowds. American Economic Journal: Microeconomics, 2(1), 112–149. https://doi.org/10.1257/mic.2.1.112

Goldstein, N. J., Cialdini, R. B., & Griskevicius, V. (2008). A room with a viewpoint: Using social norms to motivate environmental conservation in hotels. Journal of Consumer Research, 35(3), 472–482. https://doi.org/10.1086/586910

Gómez, S., Díaz-Guilera, A., Gómez-Gardeñes, J., Pérez-Vicente, C. J., Moreno, Y., & Arenas, A. (2013). Diffusion dynamics on multiplex networks. Physical Review Letters, 110(2), 028701. https://doi.org/10.1103/PhysRevLett.110.028701

Granovetter, M. (1978). Threshold models of collective behavior. American Journal of Sociology, 83(6), 1420–1443. https://doi.org/10.1086/226707

Griskevicius, V., Tybur, J. M., & Van den Bergh, B. (2010). Going green to be seen: Status, reputation, and conspicuous conservation. Journal of Personality and Social Psychology, 98(3), 392–404. https://doi.org/10.1037/a0019382

Han, H., Hsu, L.-T., & Sheu, C. (2010). Application of the theory of planned behavior to green hotel choice: Testing the effect of environmental friendly activities. Tourism Management, 31(3), 325–334. https://doi.org/10.1016/j.tourman.2009.03.013

Hegselmann, R., & Krause, U. (2002). Opinion dynamics and bounded confidence models, analysis, and simulation. Journal of Artificial Societies and Social Simulation, 5(3), 1–33. https://jasss.soc.surrey.ac.uk/5/3/2.html

Kaiser, F. G., Wölfing, S., & Fuhrer, U. (1999). Environmental attitude and ecological behaviour. Journal of Environmental Psychology, 19(1), 1–19. https://doi.org/10.1006/jevp.1998.0107

Katz, E., & Lazarsfeld, P. F. (1955). Personal influence: The part played by people in the flow of mass communications. Free Press.

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., & Porter, M. A. (2014). Multilayer networks. Journal of Complex Networks, 2(3), 203–271. https://doi.org/10.1093/comnet/cnu016

Kollmuss, A., & Agyeman, J. (2002). Mind the gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? Environmental Education Research, 8(3), 239–260. https://doi.org/10.1080/13504620220145401

Lee, K. (2011). The role of media exposure, social exposure and biospheric value orientation in the environmental attitude–intention–behaviour model in adolescents. Journal of Environmental Psychology, 31(4), 301–308. https://doi.org/10.1016/j.jenvp.2011.08.004

Lorenz, J. (2007). Continuous opinion dynamics under bounded confidence: A survey. International

Journal of Modern Physics C, 18(12), 1819–1838. https://doi.org/10.1142/S0129183107011789

Lorenz, J., Rauhut, H., Schweitzer, F., & Helbing, D. (2011). How social influence can undermine the wisdom of crowd effect. Proceedings of the National Academy of Sciences, 108(22), 9020–9025. https://doi.org/10.1073/pnas.1008636108

Lorenzoni, I., Nicholson-Cole, S., & Whitmarsh, L. (2007). Barriers perceived to engaging with climate change among the UK public and their policy implications. Global Environmental Change, 17(3–4), 445–459. https://doi.org/10.1016/j.gloenvcha.2007.01.004

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. Review of Economic Studies, 60(3), 531–542. https://doi.org/10.2307/2298123

Newman, M. E. J. (2003). The structure and function of complex networks. SIAM Review, 45(2), 167–256. https://doi.org/10.1137/S003614450342480

Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2008). Normative social influence is underdetected. Personality and Social Psychology Bulletin, 34(7), 913–923. https://doi.org/10.1177/0146167208316691

Noppers, E. H., Keizer, K., Bolderdijk, J. W., & Steg, L. (2014). The adoption of sustainable innovations: Driven by symbolic and environmental motives. Global Environmental Change, 25, 52–62. https://doi.org/10.1016/j.gloenvcha.2014.01.012

Nowak, M. A. (2006). Five rules for the evolution of cooperation. Science, 314(5805), 1560–1563. https://doi.org/10.1126/science.1133755

Nowak, M. A., & May, R. M. (1992). Evolutionary games and spatial chaos. Nature, 359(6398), 826–829. https://doi.org/10.1038/359826a0

Ohtomo, S., & Hirose, Y. (2007). The dual-process of reactive and intentional decision-making involved in eco-friendly behavior. Journal of Environmental Psychology, 27(2), 117–125. https://doi.org/10.1016/j.jenvp.2007.01.005

Ostrom, E. (1990). Governing the commons: The evolution of institutions for collective action. Cambridge University Press.

Perc, M., Jordan, J. J., Rand, D. G., Wang, Z., Boccaletti, S., & Szolnoki, A. (2017). Statistical physics of human cooperation. Physics Reports, 687, 1–51. https://doi.org/10.1016/j.physrep.2017.05.004

Perc, M., & Szolnoki, A. (2010). Coevolutionary games—A mini review. BioSystems, 99(2), 109–125. https://doi.org/10.1016/j.biosystems.2009.10.003

Pretty, J. (2003). Social capital and the collective management of resources. Science, 302(5652), 1912–1914. https://doi.org/10.1126/science.1090847

Rand, D. G., Nowak, M. A., Fowler, J. H., & Christakis, N. A. (2014). Static network structure can stabilize human cooperation. Proceedings of the National Academy of Sciences, 111(48), 17093–17098. https://doi.org/10.1073/pnas.1400747111

Roca, C. P., Cuesta, J. A., & Sánchez, A. (2009). Evolutionary game theory: Temporal and spatial effects beyond replicator dynamics. Physics of Life Reviews, 6(4), 208–249. https://doi.org/10.1016/j.plrev.2009.06.001

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., & Foley, J. A. (2009). A safe operating space for humanity. Nature, 461(7263), 472–475. https://doi.org/10.1038/461472a

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

Ryan, B., & Gross, N. C. (1943). The diffusion of hybrid seed corn in two Iowa communities. Rural Sociology, 8(1), 15–24.

Sachs, J. D. (2012). From millennium development goals to sustainable development goals. The Lancet, 379(9832), 2206–2211. https://doi.org/10.1016/S0140-6736(12)60685-0

Santos, F. C., & Pacheco, J. M. (2005). Scale-free networks provide a unifying framework for the emergence of cooperation. Physical Review Letters, 95(9), 098104. https://doi.org/10.1103/PhysRevLett.95.098104

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. Psychological Science, 18(5), 429–434. https://doi.org/10.1111/j.1467-9280.2007.01917.x

Schwartz, S. H. (1977). Normative influences on altruism. Advances in Experimental Social Psychology, 10, 221–279. https://doi.org/10.1016/S0065-2601(08)60358-5

Steg, L., & Vlek, C. (2009). Encouraging pro-environmental behaviour: An integrative review and research agenda. Journal of Environmental Psychology, 29(3), 309–317. https://doi.org/10.1016/j.jenvp.2008.10.004

Stern, P. C. (2000). New environmental theories: Toward a coherent theory of environmentally significant behavior. Journal of Social Issues, 56(3), 407–424. https://doi.org/10.1111/0022-4537.00175

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-belief-norm theory of support for social movements: The case of environmentalism. Human Ecology Review, 6(2), 81–97.

Sznajd-Weron, K., & Sznajd, J. (2000). Opinion evolution in closed community. International Journal of Modern Physics C, 11(6), 1157–1165. https://doi.org/10.1142/S0129183100000936

Thøgersen, J., & Ölander, F. (2002). Human values and the emergence of a sustainable consumption pattern: A panel study. Journal of Economic Psychology, 23(5), 605–630. https://doi.org/10.1016/S0167-4870(02)00120-4

Triandis, H. C. (1977). Interpersonal behavior. Brooks/Cole.

Valente, T. W. (1996). Social network thresholds in the diffusion of innovations. Social Networks, 18(1), 69–89. https://doi.org/10.1016/0378-8733(95)00249-9

Wang, Z., Szolnoki, A., & Perc, M. (2012). Evolution of public cooperation on interdependent networks:

The impact of biased utility functions. Europhysics Letters, 97(4), 48001. https://doi.org/10.1209/0295-5075/97/48001

Watts, D. J. (2004). Six degrees: The science of a connected age. W. W. Norton.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. Nature, 393(6684), 440–442. https://doi.org/10.1038/30918

Weisbuch, G., Deffuant, G., Amblard, F., & Nadal, J. P. (2002). Meet, discuss, and segregate! Complexity, 7(3), 55–63. https://doi.org/10.1002/cplx.10031

Whitmarsh, L. (2009). Behavioural responses to climate change: Asymmetry of intentions and impacts. Journal of Environmental Psychology, 29(1), 13–23. https://doi.org/10.1016/j.jenvp.2008.05.003

Xiao, C., & Hong, D. (2010). Gender differences in environmental behaviors in China. Population and Environment, 32(1), 88–104. https://doi.org/10.1007/s11111-010-0121-6

Zhang, X., Shi, J., & Ma, S. (2020). Factors influencing environmentally friendly behavior of urban residents: A case study. Resources, Conservation and Recycling, 155, 104685. https://doi.org/10.1016/j.resconrec.2019.104685