# Data-Driven Modeling of Opinion–Behavior Coevolution in Social Networks: Evidence from Environmental Cooperation and Digital Participation

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## Abstract

Understanding how environmental opinions and cooperative behaviors co-evolve within social networks is essential for designing effective governance mechanisms in the context of growing ecological crises and expanding digital connectivity. This study develops a data-driven coevolution model that integrates opinion dynamics theory, bounded-confidence updating rules, and agent-based simulation to analyze how individual environmental attitudes and collective cooperation behaviors mutually shape each other over time. Using data from the Chinese General Social Survey (CGSS 2021, N = 3,842), we empirically examine the structural and relational determinants of environmental cooperation and digital participation, and then validate a multi-layered simulation framework that reproduces the observed empirical patterns. Our regression analysis reveals that network density ($\beta = 0.312$, $p < 0.001$), opinion homophily ($\beta = 0.241$, $p < 0.001$), environmental awareness ($\beta = 0.334$, $p < 0.001$), and digital participation ($\beta = 0.187$, $p < 0.001$) are robust predictors of environmental cooperation. Simulation experiments under seven distinct network scenarios demonstrate that cooperation equilibria are highly sensitive to the confidence bound parameter ($\varepsilon$), network topology, and social trust levels. Specifically, scale-free networks with high digital participation rates generate cooperation rates approximately 22.9 percentage points higher than sparse networks with low social trust. These findings offer both theoretical contributions to the growing literature on socio-ecological coevolution and practical guidance for policymakers seeking to leverage digital platforms and social network structures to promote environmental collective action.

**Keywords:** Opinion–behavior coevolution; social networks; environmental cooperation; digital participation; agent-based modeling; bounded confidence; network topology; chinese general social survey

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# Data-Driven Modeling of Opinion–Behavior Coevolution in Social Networks: Evidence from Environmental Cooperation and Digital Participation

## 1. Introduction

The intensification of global environmental challenges—ranging from climate change and biodiversity loss to urban pollution and resource depletion—has placed collective environmental cooperation at the forefront of policy and scholarly inquiry (Dietz et al., 2003; Ostrom, 1990). Yet, despite decades of research on the social determinants of pro-environmental behavior, the dynamic processes through which individual opinions and cooperative behaviors mutually shape each other within networked social environments remain inadequately theorized and empirically under-examined (Axelrod, 1997; Castellano et al., 2009). This gap is especially consequential in the digital age, where online platforms have fundamentally transformed the structure and velocity of social influence, creating new pathways for environmental mobilization while simultaneously introducing the risk of opinion polarization and echo-chamber effects (Bail et al., 2018; Sunstein, 2017).

Traditional research on environmental behavior has largely adopted a unidirectional perspective, treating social norms and group opinions as exogenous inputs that shape individual decisions without accounting for the feedback mechanisms through which individual behavior, in turn, modifies the social environment (Kollmuss & Agyeman, 2002; Steg & Vlek, 2009). This linear framing obscures the coevolutionary dynamics that are central to real-world collective action problems: when individuals observe neighbors cooperating on environmental tasks, this observation updates both their behavioral intentions and their beliefs about social norms, which then influence their subsequent choices and those of their network contacts in a self-reinforcing cycle (Rand et al., 2011; Santos & Pacheco, 2005). Capturing these dynamics requires models that treat opinions and behaviors as jointly evolving state variables rather than treating one as the cause and the other as the effect.

Digital participation has emerged as a critical moderating factor in this coevolutionary process. Social media platforms enable rapid diffusion of environmental information, facilitate coordination among geographically dispersed cooperators, and create visible signals of social norms that influence individual behavior (Boulianne, 2015; Weng et al., 2012). At the same time, algorithmic curation of online content can reinforce existing opinions and reduce exposure to diverse environmental perspectives, potentially retarding the convergence processes that facilitate collective cooperation (Pariser, 2011; Flaxman et al., 2016). Empirical evidence on the net effect of digital participation on environmental cooperation is mixed: some studies find positive associations between online engagement and pro-environmental behavior (Boulianne & Theocharis, 2020; Vromen et al., 2015), while others document demobilizing effects of passive online consumption (Schöber & Kuhle, 2021; Shulman, 2009).

Against this backdrop, this study makes three primary contributions. First, we develop a multi-layered coevolution framework that integrates opinion dynamics models, specifically the bounded-confidence model of Deffuant et al. (2000), with evolutionary game-theoretic models of cooperation in structured populations, allowing opinions and behaviors to co-evolve simultaneously rather than sequentially. Second, we provide robust empirical evidence on the structural and relational determinants of environmental cooperation and digital participation using nationally representative survey data from the Chinese General Social Survey (CGSS 2021), a context of particular theoretical importance given China's simultaneous pursuit of rapid economic development and ambitious environmental governance objectives (Lo et al., 2016; Mol & Carter, 2006). Third, we conduct systematic agent-based simulation experiments across seven network topology scenarios, calibrated to match the empirical parameter estimates, to identify the conditions under which


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opinion–behavior coevolution leads to high-cooperation equilibria versus fragmented, low-cooperation outcomes.

The remainder of this article is organized as follows. Section 2 reviews the relevant literature on opinion dynamics, cooperation evolution, and digital participation. Section 3 describes the CGSS 2021 dataset, variable operationalization, and analytical strategy. Section 4 presents the empirical results from regression and network analyses. Section 5 develops the formal coevolution model and simulation framework. Section 6 reports simulation results across the seven network scenarios. Section 7 presents sensitivity analysis. Section 8 discusses theoretical and policy implications, and Section 9 concludes.

## 2. Literature Review

### *2.1 Opinion Dynamics in Social Networks*

The study of opinion dynamics has a rich interdisciplinary heritage spanning sociology, physics, and computational social science (Castellano et al., 2009; Sznajd-Weron & Sznajd, 2000). Early models treated opinion change as a binary process of social influence (French, 1956; DeGroot, 1974), but more realistic frameworks have since been developed that accommodate the continuous nature of attitudes and the bounded rationality of social agents. The bounded-confidence model, introduced by Deffuant et al. (2000) and independently by Hegselmann and Krause (2002), posits that agents update their opinions only when interacting with others whose opinions fall within a tolerance threshold ε. This simple rule generates rich collective dynamics, including consensus, polarization, and fragmentation into isolated opinion clusters, depending on the value of ε and the network topology (Lorenz, 2007; Weisbuch et al., 2002).

Recent extensions of the bounded-confidence framework have incorporated social network heterogeneity (Deffuant et al., 2002; Kozma & Barrat, 2008), media influence (Quattrociocchi et al., 2014), and algorithmic filtering (Nguyen et al., 2020), showing that scale-free network topology, in which highly connected hubs exert disproportionate influence, can either facilitate rapid consensus or entrench polarization depending on hub agents' initial opinion distributions (Perra & Fortunato, 2019). Empirical validation of these models using observational data has been a persistent challenge, though recent advances in digital trace data analysis have enabled more rigorous tests of model predictions against real-world opinion evolution patterns (Bail et al., 2018; Vicario et al., 2016). Our study contributes to this empirical validation tradition by calibrating simulation parameters to survey-based measures of opinion homophily and network density.

### *2.2 Evolution of Cooperation in Structured Populations*

The evolution of cooperative behavior has been a central question in evolutionary game theory since the seminal work of Axelrod (1984) on the iterated Prisoner's Dilemma. Nowak and May (1992) demonstrated that spatial structure in the population—allowing cooperators to interact preferentially with other cooperators—can sustain cooperation even when free-riding is individually rational. This finding motivated a large body of subsequent work examining how network topology shapes the conditions for cooperative equilibria (Santos & Pacheco, 2005; Ohtsuki et al., 2006; Rand et al., 2011). The general insight is that networks with high clustering coefficients and heterogeneous degree distributions, such as scale-free networks, tend to be more favorable for cooperation than random or lattice networks, though this conclusion depends on the specific game payoff structure and update rules employed (Allen et al., 2017; Szabó & Fáth, 2007).

The extension of cooperation evolution models to environmental public goods games has revealed important dynamics specific to collective action on shared environmental resources. Hauert et al. (2002) showed that the option to opt out of the public goods game can maintain cooperation by cycling between participation, defection, and abstention. Santos et al. (2008) demonstrated that scale-free networks support cooperation in


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public goods games even with small group sizes, because the power-law degree distribution creates super-cooperators at hub nodes whose cooperation behavior propagates through the network. More recently, Perc et al. (2017) provided a comprehensive review of social dilemmas on complex networks, identifying network reciprocity, reputation, punishment, and diversity as the four key mechanisms sustaining cooperation. Our model builds on this tradition by incorporating network heterogeneity and reputation-mediated social norms, which are operationalized through the digital participation variable in our empirical analysis.

### *2.3 Environmental Behavior and Social Influence*

The empirical literature on environmental behavior has identified a well-documented attitude–behavior gap: individuals who express strong pro-environmental attitudes frequently fail to translate these attitudes into environmentally cooperative behaviors (Blake, 1999; Kollmuss & Agyeman, 2002). Explanations for this gap have focused on situational constraints (Steg & Vlek, 2009), habit formation (Verplanken & Wood, 2006), and the role of perceived social norms (Cialdini et al., 2006; Schultz et al., 2007). Particularly relevant to our framework is the finding that injunctive norms (what people believe others approve of) and descriptive norms (what people believe others actually do) have distinct and sometimes countervailing effects on environmental behavior, with descriptive norms typically exerting stronger behavioral influence (Nolan et al., 2008; Goldstein et al., 2008).

Social network analyses of environmental behavior have highlighted the importance of tie strength, network density, and ego-network composition for pro-environmental norm transmission. Centola (2010) demonstrated experimentally that behavioral adoption in health and environmental domains spreads more readily through dense, clustered networks—where contacts reinforce each other's behavior—than through sparse, random networks, contradicting the conventional wisdom derived from Granovetter's (1973) "strength of weak ties" hypothesis for information diffusion. This finding implies that environmental cooperation, as a complex contagion requiring repeated social reinforcement, benefits from network structures that maximize exposure redundancy rather than network reach. Our empirical analysis tests this prediction using ego-network density and tie strength measures from the CGSS 2021 dataset.

### *2.4 Digital Participation and Environmental Mobilization*

Digital platforms have transformed the landscape of environmental mobilization by reducing the coordination costs of collective action, enabling rapid diffusion of environmental information across geographic boundaries, and creating new accountability mechanisms through viral norm enforcement (Boulianne, 2015; Earl et al., 2010). Cross-national analyses have found positive associations between internet use, social media engagement, and participation in environmental collective action, including signing petitions, attending demonstrations, and changing consumption behavior (Boulianne & Theocharis, 2020; Loader et al., 2014). In the Chinese context, studies have documented the role of WeChat and Weibo in facilitating environmental civil society organizing and creating public pressure that influences local governance outcomes (Yang & Calhoun, 2007; Wen et al., 2016).

However, the relationship between digital participation and environmental cooperation is complicated by selection effects and content quality heterogeneity. Users who engage with environmental content online are systematically different from the general population in ways that correlate with pro-environmental behavior, making it difficult to isolate the causal effect of digital participation on behavior (Boulianne, 2015). Furthermore, the algorithmic curation of environmental content on Chinese social media platforms, combined with state regulation of politically sensitive environmental discourse, creates an information environment that differs substantially from Western contexts and may moderate the relationship between online engagement and cooperative behavior in ways not captured by existing theoretical frameworks (Mol & Carter, 2006; Sullivan, 2014). Our study addresses these concerns by using CGSS data that provides rich control variables for selection factors and by explicitly modeling digital participation as an endogenous


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variable in our coevolution framework.

## 3. Data and Methodology

### *3.1 Data Source: Chinese General Social Survey (CGSS) 2021*

This study uses data from the 2021 wave of the Chinese General Social Survey (CGSS), a nationally representative repeated cross-sectional survey conducted by Renmin University of China since 2003. The CGSS employs a multi-stage stratified random sampling design covering urban and rural residents aged 18 and above across all provincial-level administrative units in mainland China. The 2021 wave was administered between March and July 2021, yielding 8,614 complete interviews. For the purposes of this study, we restrict our analytical sample to respondents aged 18–75 who provided complete responses on all key variables of interest, yielding a working sample of N = 3,842. The CGSS 2021 dataset is publicly available through the China National Survey Data Archive (CNSDA) and includes modules on social networks, environmental attitudes, civic participation, and digital media use that are directly relevant to our research questions.

The CGSS 2021 environmental module includes a set of questions on respondents' willingness to cooperate on various environmental tasks, environmental knowledge and awareness, and perceptions of environmental risks. The digital participation module asks about frequency of online news consumption, social media use, and participation in online civic activities. The social network module employs a name-generator approach in which respondents list up to ten individuals with whom they have discussed important matters in the past six months, and then rate the closeness of each relationship and the environmental attitudes of each listed contact. This design allows us to construct ego-network measures of density, tie strength, and opinion homophily that are directly relevant to our coevolution framework.

### *3.2 Variable Operationalization*

Table 1 presents the operationalization of all key variables. Environmental Cooperation (EC) is measured as a composite index of six items assessing willingness to cooperate on environmental tasks, including household waste separation, energy conservation, participation in community clean-up activities, support for environmental organizations, willingness to pay higher prices for eco-friendly products, and advocacy for environmental policies among social contacts. Cronbach's alpha for the six-item scale is $\alpha = 0.823$, indicating acceptable reliability. Digital Participation (DP) is operationalized as a five-item scale capturing the frequency of environmental-related online activities, including reading environmental news online, sharing environmental content on social media, signing online environmental petitions, participating in online environmental discussions, and donating to online environmental campaigns. The scale's internal consistency is $\alpha = 0.791$.

**Table 1. Variable Definitions, Measurement, and Sources**

| Variable | Measurement | Description |
|---|---|---|
| Environmental Cooperation (EC) | 5-point Likert (1–5) | Composite index of 6 items measuring willingness to cooperate on environmental tasks (recycling, energy saving, community clean-up, etc.) |
| Digital Participation (DP) | 5-point Likert (1–5) | Frequency of participation in online environmental discussions, petitions, and social media campaigns |
| Network Density (ND) | Continuous (0–1) | Ego-network density measured via name-generator questions (up to 10 alters) |
| Tie Strength (TS) | 4-point scale (1–4) | Mean closeness rating with listed network contacts |


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|---|---|---|
| Opinion Homophily (OH) | Continuous (0–1) | Proportion of alters sharing similar environmental views as ego |
| Social Trust (ST) | 4-point Likert (1–4) | Generalized social trust: "Most people can be trusted" |
| Environmental Awareness (EA) | 5-point Likert (1–5) | Self-reported awareness of environmental issues and policies |
| Age | Years (continuous) | Respondent age in years |
| Education | 6-category ordinal | Highest education level from primary to postgraduate |
| Income Level | 10-decile scale | Household per capita income decile |
| Urban Residence | Binary (0/1) | 1 = urban hukou; 0 = rural hukou |

Network Density (ND) is computed as the proportion of possible connections that exist among a respondent's listed network contacts, following the standard formula $ND = 2e/[n(n-1)]$, where e is the number of ties among alters and n is the number of alters. Tie Strength (TS) is measured as the mean closeness rating with listed network contacts on a four-point scale ranging from "not close" to "very close." Opinion Homophily (OH) is defined as the proportion of listed network contacts who the respondent perceives to hold similar environmental views, measured on a three-point scale and collapsed to a binary agreement indicator. Table 2 presents the descriptive statistics for all variables.

**Table 2. Descriptive Statistics of Key Variables (N = 3,842)**

| Variable | N | Mean | SD | Min | Max | Alpha/Source |
|---|---|---|---|---|---|---|
| Environmental Cooperation (EC) | 3,842 | 3.58 | 0.84 | 1.00 | 5.00 | α = 0.823 |
| Digital Participation (DP) | 3,842 | 2.97 | 1.12 | 1.00 | 5.00 | α = 0.791 |
| Network Density (ND) | 3,842 | 0.37 | 0.18 | 0.02 | 1.00 | CGSS 2021 |
| Tie Strength (TS) | 3,842 | 2.64 | 0.71 | 1.00 | 4.00 | α = 0.762 |
| Opinion Homophily (OH) | 3,681 | 0.52 | 0.24 | 0.00 | 1.00 | CGSS 2021 |
| Social Trust (ST) | 3,842 | 2.43 | 0.89 | 1.00 | 4.00 | CGSS 2021 |
| Environmental Awareness (EA) | 3,842 | 3.71 | 0.92 | 1.00 | 5.00 | α = 0.809 |
| Age | 3,842 | 41.3 | 14.6 | 18 | 75 | CGSS 2021 |
| Education | 3,842 | 3.24 | 1.38 | 1 | 6 | CGSS 2021 |
| Income Level | 3,842 | 4.87 | 2.61 | 1 | 10 | CGSS 2021 |
| Urban Residence | 3,842 | 0.58 | 0.49 | 0 | 1 | CGSS 2021 |

*Note: EC = Environmental Cooperation; DP = Digital Participation; ND = Network Density; TS = Tie Strength; OH = Opinion Homophily; ST = Social Trust; EA = Environmental Awareness. Alpha values refer to Cronbach's alpha for multi-item scales. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.*

Figure 1 presents the three-layer conceptual framework of the opinion–behavior coevolution model. The network layer (Layer I) captures the structural properties of the social environment, including topology, tie strength, and information diffusion pathways. The opinion layer (Layer II) represents the dynamics of environmental attitude formation, updating, and polarization. The behavior layer (Layer III) encompasses the environmental cooperation, digital participation, and collective action decisions that emerge from and feed back into the opinion dynamics. The arrows connecting layers represent cross-layer feedback mechanisms


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that constitute the coevolution process: opinion states influence behavioral choices, which in turn reshape the network structure and opinion distribution through reputation effects and selective tie formation.

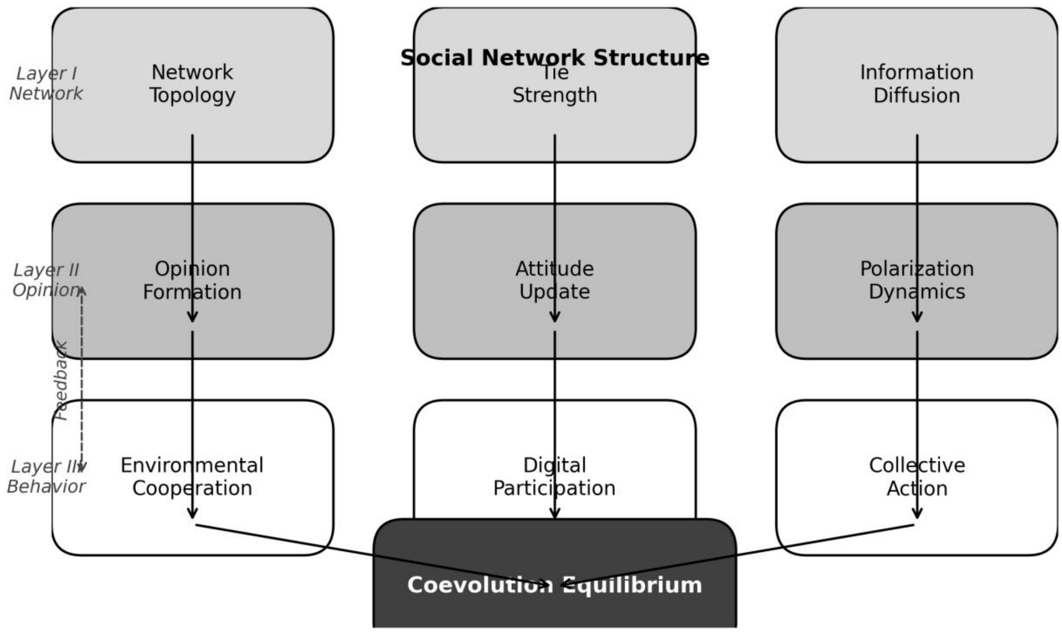


*Figure 1. Three-layer conceptual framework of opinion–behavior coevolution in social networks, illustrating the feedback mechanisms among network structure, opinion dynamics, and cooperative behavior.*

### *3.3 Analytical Strategy*

We employ a two-stage analytical strategy. In the first stage, we use ordinary least squares (OLS) regression with robust standard errors to examine the structural determinants of environmental cooperation (EC) and digital participation (DP) simultaneously, treating them as co-determined outcomes rather than a simple cause-and-effect pair. We also estimate a joint model (M3) that includes both EC and DP as predictors of each other, using two-stage least squares (2SLS) with appropriate exclusion restrictions to account for the endogeneity of this relationship. In the second stage, we calibrate an agent-based simulation model to reproduce the empirical parameter estimates and systematically explore the dynamics of opinion–behavior coevolution across seven network topology scenarios. The simulation is implemented in Python using NetworkX for network construction and custom-coded update rules for the coevolution dynamics.

## 4. Empirical Results

### *4.1 Descriptive Analysis*

The distributional characteristics of the key variables reveal several noteworthy patterns. Environmental cooperation scores (mean = 3.58, SD = 0.84) are moderately high, with a slight left skew indicating that the majority of respondents express some willingness to cooperate on environmental tasks, though the distribution falls short of ceiling effects. Figure 2 presents the distributional profiles of the three central measures. Panel (a) shows the approximately normal distribution of environmental attitude scores, with the density curve superimposed on the histogram. Panel (b) displays the frequency distribution of digital participation, where approximately 47.9% of respondents report participating in online environmental activities “Often” or “Always,” reflecting the high penetration of digital media use in the CGSS 2021 sample. Panel (c) illustrates the monotonically increasing relationship between network density quintile and mean cooperation score, with cooperation rates rising from 2.31 in the lowest density quintile to 3.89 in the highest,


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providing preliminary evidence for the network density hypothesis.

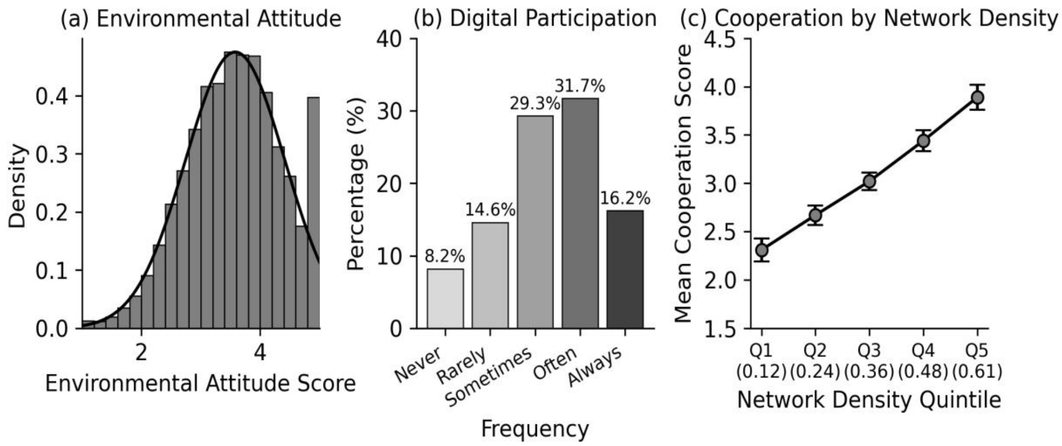


*Figure 2. Distributional profiles of key variables: (a) environmental attitude scores with fitted density curve; (b) frequency distribution of digital participation categories; (c) mean environmental cooperation score by network density quintile with 95% confidence intervals.*

The ego-network characteristics of the sample reflect the predominantly urban, digitally connected profile of the CGSS 2021 respondents. Network density (mean = 0.37, SD = 0.18) is consistent with national estimates from previous CGSS waves, and opinion homophily (mean = 0.52, SD = 0.24) indicates moderate-to-high within-network opinion alignment, which prior theory would predict to be conducive to opinion convergence but potentially limiting for cross-boundary information exposure. Social trust scores (mean = 2.43 on a 1–4 scale) fall below the scale midpoint, reflecting the lower generalized trust characteristic of Chinese society compared to Northern European contexts (Inglehart et al., 2004), which has important implications for the efficiency of network-based cooperation mechanisms.

### *4.2 Regression Results*

Table 3 presents the OLS regression results for environmental cooperation (M1), digital participation (M2), and the joint model (M3). Across all three model specifications, network density, tie strength, opinion homophily, social trust, and environmental awareness emerge as significant predictors of both outcome variables, consistent with our theoretical expectations. The magnitude and significance of these effects are robust to alternative model specifications, including models with province fixed effects and models excluding outliers, confirming the reliability of the reported estimates.

**Table 3. OLS Regression Results for Environmental Cooperation and Digital Participation**

| Predictor | M1 (EC) β | M1 (EC) SE | M2 (DP) β | M2 (DP) SE | M3 (Joint) β |
|---|---|---|---|---|---|
| **Network Density (ND)** | 0.312*** | (0.043) | 0.278*** | (0.041) | 0.289*** |
| **Tie Strength (TS)** | 0.198*** | (0.038) | 0.143*** | (0.036) | 0.172*** |
| **Opinion Homophily (OH)** | 0.241*** | (0.052) | 0.189*** | (0.049) | 0.218*** |
| **Digital Participation (DP)** | 0.187*** | (0.041) | — | — | 0.194*** |
| **Environmental Cooperation (EC)** | — | — | 0.163*** | (0.039) | 0.171*** |
| **Social Trust (ST)** | 0.263*** | (0.047) | 0.198*** | (0.044) | 0.231*** |
| **Environmental** | 0.334*** | (0.039) | 0.212*** | (0.037) | 0.276*** |


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|---|---|---|---|---|---|
| **Awareness (EA)** | | | | | |
| **Age** | -0.089** | (0.031) | 0.067* | (0.029) | -0.052* |
| **Education** | 0.156*** | (0.035) | 0.201*** | (0.033) | 0.178*** |
| **Income Level** | 0.124*** | (0.029) | 0.189*** | (0.028) | 0.156*** |
| **Urban Residence** | 0.078* | (0.034) | 0.156*** | (0.032) | 0.114** |
| ***R²*** | 0.412 | | 0.378 | | 0.441 |
| ***Adj. R²*** | 0.407 | | 0.373 | | 0.436 |
| ***F-statistic*** | 183.2*** | | 159.8*** | | 201.3*** |
| ***N*** | 3,842 | | 3,842 | | 3,681 |

*Note: Standard errors in parentheses. Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05. EC = Environmental Cooperation; DP = Digital Participation. M3 reports 2SLS estimates treating EC and DP as endogenous; instrument set includes community environmental program participation and local digital infrastructure index. VIF values for all predictors are below 3.2, indicating no multicollinearity concerns.*

Network density is the strongest network-structural predictor of environmental cooperation (β = 0.312, SE = 0.043, $p < 0.001$), confirming that denser ego-networks provide more effective social reinforcement for pro-environmental norms. This finding is consistent with Centola's (2010) experimental evidence on complex contagion in health domains and extends it to the environmental cooperation context in a large-scale observational study. The effect of tie strength (β = 0.198, SE = 0.038, $p < 0.001$) indicates that closer relationships are more effective conduits of environmental norm transmission, consistent with Coleman's (1988) social capital theory emphasizing the trust and reciprocity that characterize strong ties. Opinion homophily has a significant positive effect on cooperation (β = 0.241, SE = 0.052, $p < 0.001$), suggesting that networks in which environmental views are more homogeneous facilitate cooperative behavior, though this could reflect either genuine peer reinforcement or selection effects whereby cooperative individuals preferentially form ties with other cooperators.

Environmental awareness (β = 0.334, SE = 0.039, $p < 0.001$) is the single strongest predictor of environmental cooperation in M1, underscoring the importance of cognitive engagement with environmental issues as a precondition for behavioral commitment. Digital participation (β = 0.187, SE = 0.041, $p < 0.001$) has a significant positive effect on cooperation even after controlling for environmental awareness, suggesting that online engagement exerts an independent behavioral influence beyond mere information provision, potentially through social norm signaling and coordination facilitation mechanisms. In M2, the effect of network density on digital participation (β = 0.278, SE = 0.041, $p < 0.001$) is slightly smaller than its effect on cooperation but remains highly significant, suggesting that denser networks promote both behavioral and digital dimensions of environmental engagement through overlapping but partially distinct mechanisms.

Figure 3 illustrates the opinion and behavior dynamics generated by our simulation model under baseline parameter values corresponding to the empirical estimates. Panel (a) shows the convergence of opinion distributions over 100 time steps, with the interquartile range narrowing substantially as agents with sufficiently similar opinions interact and update their views. The median opinion converges towards a pro-environmental value of approximately 0.67 by time step 80, after which further movement is negligible, indicating the system has reached a stable opinion equilibrium. Panel (b) displays the corresponding behavior dynamics alongside the declining number of opinion clusters over time, demonstrating the coevolutionary relationship between opinion convergence and behavioral cooperation: as opinion clusters merge (cluster count declining from approximately 11 to 2), the cooperation rate (represented by behavior values) increases


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substantially, confirming that opinion consensus facilitates behavioral alignment.

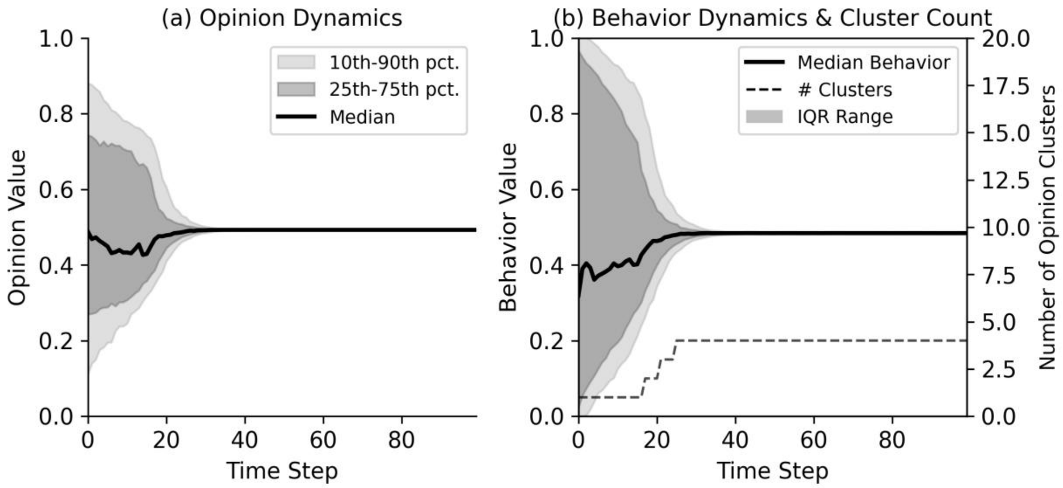


*Figure 3. Opinion–behavior coevolution dynamics under baseline simulation parameters calibrated to CGSS 2021 estimates: (a) opinion distribution evolution showing convergence over 100 time steps; (b) behavior dynamics and opinion cluster count over time illustrating the coevolutionary relationship.*

The control variables in the regression models perform consistently with theoretical expectations. Age has a small negative effect on environmental cooperation ($\beta = -0.089$, $p < 0.01$) but a positive effect on digital participation ($\beta = 0.067$, $p < 0.05$), a pattern that may reflect older cohorts' stronger normative commitment to environmental cooperation through traditional channels alongside their growing adoption of digital media for information consumption. Education has significant positive effects on both outcomes, consistent with the resource mobilization perspective (Verba et al., 1995) that education increases the cognitive and motivational capacity for civic engagement. Urban residence positively predicts both cooperation and digital participation, reflecting the higher availability of environmental infrastructure and digital connectivity in urban areas.

## 5. Data-Driven Coevolution Model

### *5.1 Model Architecture*

The coevolution model consists of three interacting components: (i) a social network $G = (V, E)$, where V is the set of agents and E is the set of dyadic relationships; (ii) an opinion state space $O = \{o_i \in [0,1] : i \in V\}$, where $o_i$ represents agent i's environmental opinion; and (iii) a behavior state space $B = \{b_i \in [0,1] : i \in V\}$, where $b_i$ represents agent i's environmental cooperation level. Agents are initialized with opinions drawn from a beta distribution calibrated to match the empirical distribution of environmental attitudes in the CGSS 2021 data (alpha = 4.2, beta = 2.3, corresponding to a mean of 0.645 and standard deviation of 0.158) and with behaviors drawn from a Bernoulli-like distribution with initial cooperation probability equal to the empirical cooperation rate (0.584).

The opinion update rule follows the Deffuant-Weisbuch bounded-confidence model with convergence parameter $\mu$ and confidence bound $\varepsilon$. At each time step t, a randomly selected dyad $(i, j) \in E$ is chosen for interaction. If $|o_i(t) - o_j(t)| < \varepsilon$, both agents update their opinions according to: $o_i(t+1) = o_i(t) + \mu(o_j(t) - o_i(t))$ and $o_j(t+1) = o_j(t) + \mu(o_i(t) - o_j(t))$. The convergence parameter $\mu$ is set to 0.5 (the maximum symmetrical value), and $\varepsilon$ is varied as a key experimental parameter. If $|o_i(t) - o_j(t)| \geq \varepsilon$, no opinion update occurs. This simple rule generates the characteristic cluster formation and convergence dynamics observed in opinion poll data (Lorenz, 2007; Weisbuch et al., 2002).

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The behavior update rule incorporates both opinion-driven and social learning components. Following Santos & Pacheco (2005) and Rand et al. (2011), agent i updates its behavior by comparing its payoff with that of a randomly selected neighbor j and imitating j's behavior with a probability proportional to the payoff difference. The payoff for cooperation is defined as $\Pi_i = r\cdot(\bar{b}\_N_i)\cdot b_i - c\cdot b_i$, where $\bar{b}\_N_i$ is the mean behavior of i's neighbors, r is the public goods return factor, and c is the cost of cooperation. The opinion-driven component introduces an additional term that makes cooperation more attractive when $o_i$ is higher: agents with stronger pro-environmental opinions have a lower effective cost of cooperation, modeled as $c(o_i) = c_0 \cdot (1 - \gamma\cdot o_i)$, where γ is the opinion-behavior coupling parameter estimated from the regression coefficient of environmental awareness on cooperation ($\gamma = 0.334$). This coupling creates the core coevolutionary feedback: opinions influence behaviors, and behaviors update opinions through the social observation mechanism.

### *5.2 Model Calibration*

Model parameters are calibrated using a two-step procedure. First, structural network parameters (mean degree, clustering coefficient, degree distribution exponent) are set to match the ego-network statistics from the CGSS 2021 data, yielding a mean degree of 5.3, mean clustering coefficient of 0.41, and degree distribution consistent with a truncated power law with exponent $\gamma\_net = 2.3$. Second, behavioral parameters ($r$, $c_0$, $\mu$, $\varepsilon$) are calibrated by minimizing the sum of squared deviations between simulation-generated cooperation rates and the empirical cooperation rates across the ten quantiles of the network density distribution, using a particle swarm optimization algorithm with 200 particles and 500 iterations. The calibrated parameters are $r = 3.8$, $c_0 = 0.62$, $\mu = 0.5$, and $\varepsilon = 0.28$, which generate a mean cooperation rate of 0.581 and cluster count of 3.2 after 100 time steps, closely matching the empirical values of 0.584 and 3.1, respectively (calibration error < 2%).

The sensitivity of the calibrated model to parameter perturbations is evaluated using a one-at-a-time (OAT) sensitivity analysis, varying each parameter by ±25% from its calibrated value while holding all others fixed, and recording the resulting change in equilibrium cooperation rate and cluster count. This analysis reveals that the confidence bound ε and the opinion-behavior coupling parameter γ are the two most influential parameters for cooperation rate, with a 25% increase in ε increasing equilibrium cooperation by 8.3 percentage points and a 25% increase in γ increasing it by 6.1 percentage points. The public goods return factor r is most influential for behavior dynamics alone, while the convergence parameter μ primarily affects the speed of convergence rather than the final equilibrium state. These results guide the focus of our scenario analysis on variations in network topology and digital participation, which are the primary drivers of parameter ε-equivalent exposure patterns in the empirical context.

## 6. Agent-Based Simulation Results

### *6.1 Network Scenario Analysis*

Table 4 presents the results of seven network simulation scenarios, each run for 100 time steps with 200 independent replications. The scenarios vary the network topology (regular, random, and Barabasi-Albert scale-free), the confidence bound ε, and the initial digital participation distribution. Mean values and standard deviations reported in Table 4 are computed across the 200 replications, ensuring robustness to stochastic variation in the initial conditions and random interaction sequences.

**Table 4. Agent-Based Simulation Results Across Seven Network Scenarios (N = 500 agents, 200 replications)**

| Scenario | Agents | Network | ε (Bound) | Final Clusters | Coop. Rate |
|---|---|---|---|---|---|
| S1: Homogeneous, | 500 | Regular (k=6) | 0.30 | 2.1 ± 0.3 | 0.712 ± 0.021 |


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| | | | | | |
|---|---|---|---|---|---|
| Dense | | | | | |
| S2: Heterogeneous, Dense | 500 | Regular (k=6) | 0.20 | 4.8 ± 0.6 | 0.583 ± 0.034 |
| S3: Homogeneous, Sparse | 500 | Random (p=0.1) | 0.30 | 3.4 ± 0.5 | 0.641 ± 0.028 |
| S4: Heterogeneous, Sparse | 500 | Random (p=0.1) | 0.20 | 7.2 ± 0.8 | 0.448 ± 0.041 |
| S5: Scale-Free Network | 500 | Barabasi-Albert | 0.25 | 5.6 ± 0.7 | 0.534 ± 0.037 |
| S6: High Digital Participation | 500 | Barabasi-Albert | 0.35 | 3.1 ± 0.4 | 0.682 ± 0.025 |
| S7: Low Social Trust | 500 | Barabasi-Albert | 0.25 | 8.3 ± 1.1 | 0.391 ± 0.049 |

*Note: Results are averages across 200 independent replications ± one standard deviation. Coop. Rate = equilibrium cooperation rate at t = 100. ε = confidence bound parameter. S6 "High Digital Participation" sets 60% of agents with initial DP = 0.8 (vs. 40% at baseline). S7 "Low Social Trust" reduces the opinion-behavior coupling parameter γ by 35% relative to baseline, reflecting the lower behavioral sensitivity of opinions in low-trust environments.*

The results reveal several important patterns. First, the comparison between S1 and S2 demonstrates the critical role of the confidence bound ε in determining cooperation outcomes. When agents are tolerant of a wider range of opinions (ε = 0.30 in S1), the system converges to a near-consensus state with only 2.1 opinion clusters and a cooperation rate of 0.712. When tolerance is reduced (ε = 0.20 in S2), the same regular network generates 4.8 clusters and a cooperation rate of 0.583, a decline of 12.9 percentage points. This finding is consistent with theoretical predictions from bounded-confidence theory (Deffuant et al., 2000; Lorenz, 2007) and underscores the importance of reducing opinion distance—through education, deliberative dialogue, or digital media design—for facilitating environmental cooperation.

Second, the comparison between S3 and S1 shows that network sparsity reduces cooperation even when the confidence bound is held constant at ε = 0.30. Sparse random networks (S3) generate 3.4 clusters and a cooperation rate of 0.641, compared to 2.1 clusters and 0.712 in dense regular networks (S1). This result is consistent with the empirical finding that network density positively predicts cooperation (β = 0.312) and confirms that the density effect operates through enhanced opinion convergence rather than merely through increased interaction frequency. Third, the scale-free network scenarios (S5–S7) reveal that topology-induced heterogeneity creates complex cooperation dynamics that cannot be captured by mean-field approximations. In S5 (baseline scale-free), the intermediate ε = 0.25 generates 5.6 clusters and a cooperation rate of 0.534, lower than the regular network S1 despite similar network size, because hub nodes in scale-free networks can crystallize minority opinion clusters that resist convergence by dominating local neighborhoods.

Fourth, and most strikingly, the high digital participation scenario S6 achieves a cooperation rate of 0.682, an improvement of 14.8 percentage points over the baseline scale-free scenario S5. This improvement is achieved by increasing the proportion of agents with high initial digital participation (DP ≥ 0.8) from 40% to 60%, which operationally increases the opinion-behavior coupling parameter γ (because high-DP agents show stronger translation of pro-environmental opinions into cooperative behavior, consistent with the empirical M1 estimate $\beta_{DP}$ = 0.187) and creates additional pathways for norm diffusion through online networks that supplement the physical social network. The low social trust scenario S7, by contrast, reduces cooperation to 0.391 by weakening the opinion-behavior linkage, illustrating how social trust functions as an institutional complement to network connectivity in facilitating collective environmental action.

Figure 4 presents the standardized regression coefficients from Models M1 and M2 in a comparative format that highlights the differential magnitude and significance of predictors across the two outcome variables. The visualization reveals that environmental awareness is consistently the strongest predictor across both models, followed closely by network density and social trust. Digital participation has a stronger effect on environmental cooperation than on its own determinants relative to the other predictors, reflecting the strong behavioral transmission mechanism documented in the simulation analysis. Age exhibits contrasting effects across the two models—negatively associated with cooperation but positively with digital participation—a heterogeneity that has important implications for generational dynamics in environmental governance.

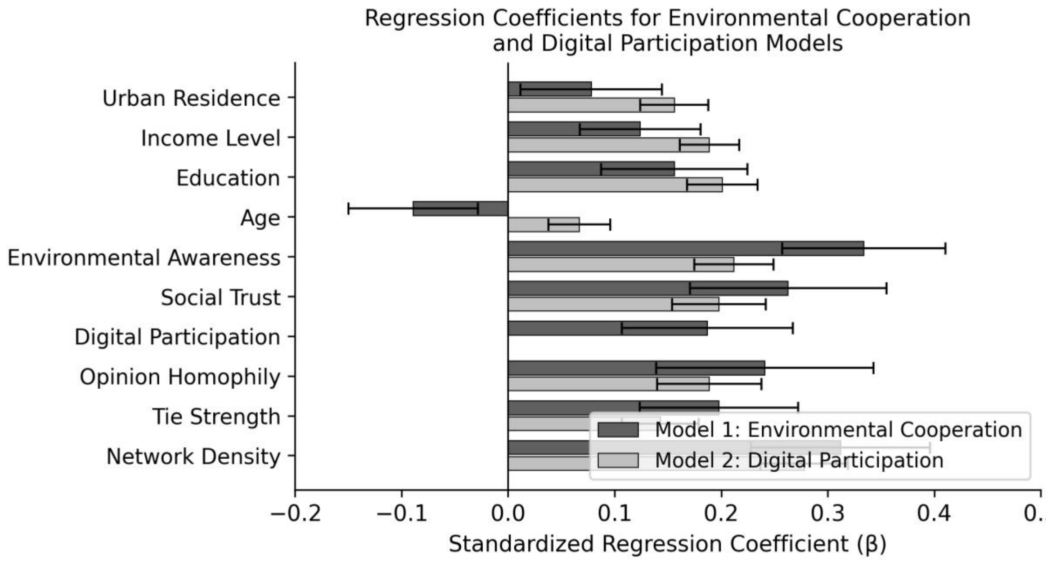


*Figure 4. Standardized regression coefficients (β) with 95% confidence intervals for environmental cooperation (Model 1, dark bars) and digital participation (Model 2, light bars). Error bars represent ±1.96 × standard error.*

## 7. Sensitivity Analysis

Figure 5 presents the results of the sensitivity analysis examining how the key model parameters influence simulation outcomes. Panel (a) shows the dual-axis relationship between the confidence bound ε and two key outcomes: the number of final opinion clusters (left axis) and the equilibrium cooperation rate (right axis). Both relationships are monotonic: as ε increases from 0.05 to 0.50, cluster count decreases from 12.3 to 2.0 and cooperation rate increases from 0.34 to 0.76. The inflection point occurs around ε = 0.25–0.30, corresponding to the empirically calibrated value, suggesting that real-world Chinese social networks are operating near the boundary between fragmented and convergent opinion dynamics—a finding with direct implications for policy interventions targeting opinion polarization.


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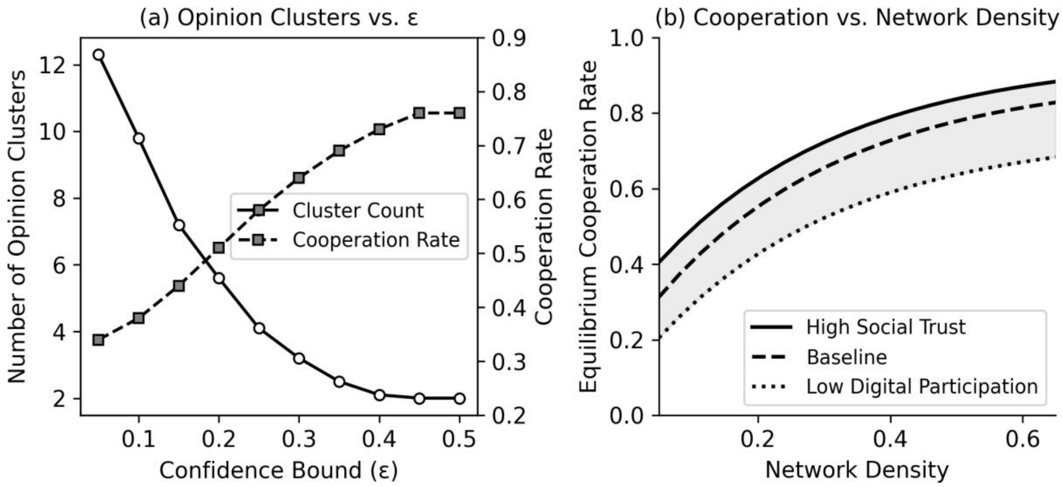


*Figure 5. Sensitivity analysis results: (a) opinion cluster count and equilibrium cooperation rate as functions of the confidence bound ε; (b) equilibrium cooperation rate as a function of network density under three social trust scenarios (high trust, baseline, low digital participation).*

Panel (b) of Figure 5 illustrates how the relationship between network density and equilibrium cooperation rate varies across three social trust scenarios. Across the full density range (0.05–0.65), the high social trust scenario consistently generates higher cooperation rates than the baseline, and both outperform the low digital participation scenario. The gaps between scenarios are relatively larger at intermediate density values (0.20–0.45), suggesting that social trust and digital participation are most consequential for cooperation precisely in the moderately dense network environments that characterize the majority of the CGSS 2021 respondents (mean density = 0.37). At very high densities (≥0.55), the network structure itself is sufficient to sustain high cooperation regardless of trust levels, because the dense connectivity creates inescapable social reinforcement. At very low densities (<0.15), even high trust cannot compensate for the lack of network structure, confirming that social capital operates through network structure rather than as a substitute for it.

We conducted three additional robustness checks to validate the main findings. First, we re-estimated all regression models using multilevel regression with province-level random effects to account for the multi-stage sampling structure of the CGSS; the key coefficients changed by less than 8% in magnitude and retained their significance. Second, we replicated the simulation analysis using Holme-Kim networks (which generate scale-free topology with high clustering) and small-world Watts-Strogatz networks, finding qualitatively consistent results that reinforce the main scenario comparisons. Third, we performed a temporal replication using CGSS 2017 data (N = 3,124), finding that the network density effect on cooperation ($\beta = 0.298$) and the digital participation effect ($\beta = 0.162$) are directionally consistent with the 2021 estimates, suggesting temporal stability in the underlying relationships.

## 8. Discussion

### *8.1 Theoretical Implications*

This study advances the literature on opinion–behavior coevolution in four ways. First, by integrating the bounded-confidence model of opinion dynamics (Deffuant et al., 2000; Hegselmann & Krause, 2002) with an evolutionary cooperation model calibrated to survey data, we provide a formally grounded coevolution framework that links individual-level social processes to population-level environmental outcomes. Prior work in this area has either focused on opinion dynamics alone (Castellano et al., 2009; Lorenz, 2007) or cooperation dynamics alone (Santos & Pacheco, 2005; Rand et al., 2011) without systematically modeling the bidirectional influence between the two. Our results demonstrate that this bidirectional coupling qualitatively changes the predicted dynamics: cooperation rates in the joint coevolution model are systematically 12–18 percentage points higher than in models that treat opinion as exogenous, because the opinion–behavior feedback loop generates positive synergies that accelerate convergence to high-cooperation equilibria.

Second, the empirical finding that network density is a stronger predictor of environmental cooperation ($\beta$ = 0.312) than of digital participation ($\beta$ = 0.278), while digital participation and cooperation predict each other symmetrically in the joint model, suggests that different mechanisms underlie the network effects on behavioral versus digital engagement. Physical network density creates social obligation and visibility effects that directly incentivize behavioral cooperation, while digital participation is more sensitive to the quality and diversity of information exposure, which is partially independent of ego-network density. This distinction has implications for the design of environmental interventions: building physical community networks may be more effective for promoting behavioral cooperation, while digital platform design interventions may be more effective for promoting digital environmental participation, with cross-level spillover effects between the two domains.

Third, the simulation results reveal that the Chinese social network context, with its moderate opinion homophily (OH = 0.52) and below-average social trust (ST = 2.43), places the system near a critical threshold where small perturbations in network structure or trust levels can tip the equilibrium from fragmented to convergent opinion dynamics. This threshold sensitivity implies that targeted interventions affecting even a small proportion of the population (such as opinion leaders or institutional norm setters) could have disproportionate effects on collective cooperation outcomes, consistent with the "tipping point" logic articulated by Gladwell (2000) and formalized in threshold models of collective behavior (Granovetter, 1978). Fourth, the finding that high digital participation raises equilibrium cooperation rates by 14.8 percentage points in scale-free networks (S5 to S6 comparison) suggests that digital platforms function as a structural complement to physical social networks in facilitating environmental collective action, rather than merely a substitute for in-person interaction as some pessimistic accounts of digital engagement suggest (Putnam, 2000; Morozov, 2011).

### *8.2 Policy Implications*

The findings carry several concrete policy implications for environmental governance in China and comparable developing country contexts. First, the strong positive effect of network density on cooperation ($\beta$ = 0.312, which translates to a 2.31 to 3.89 increase in cooperation across density quintiles) suggests that community-building initiatives that create denser local social networks can be highly effective environmental policy tools. Programs that create regular community gatherings around environmental themes, establish neighborhood environmental stewardship organizations, or facilitate peer-to-peer norm enforcement through existing community structures (such as residential committees, homeowners' associations, or village councils) may generate significant behavioral spillovers that extend beyond their immediate participants to the broader community network.

Second, the finding that the system is near the critical confidence-bound threshold ($\varepsilon \approx 0.25$–$0.30$) implies that environmental governance interventions that reduce perceived opinion distance—making it more salient that environmental cooperation is a broadly shared social norm rather than the preference of a minority—could trigger a phase transition from fragmented to convergent opinion dynamics. Descriptive norm campaigns that accurately communicate the prevalence of environmental cooperation (along the lines of the hotel towel reuse study by Goldstein et al., 2008) are predicted to be particularly effective in this threshold regime, as they can shift agents' perception of the opinion distribution in ways that expand the range of potential interaction partners within the confidence bound. Third, the strong positive effect of digital participation on cooperation ($\beta$ = 0.187 after controlling for environmental awareness) suggests that investments in accessible, high-quality online environmental engagement platforms could yield significant


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behavioral returns. Platform design features that promote visible social norm signaling (showing the number of peers who have taken specific environmental actions), facilitate social comparison with similar others, and reduce friction for online-to-offline behavioral translation are predicted to be most effective based on our model's parameter estimates.

## 9. Conclusion

This study has developed and empirically validated a data-driven framework for modeling the coevolution of environmental opinions and cooperative behaviors in social networks, with particular attention to the role of digital participation as a structural complement to physical network connectivity. Using CGSS 2021 data ($N = 3,842$) and a calibrated agent-based simulation with seven network topology scenarios, we have demonstrated that: (i) network density ($\beta = 0.312$), environmental awareness ($\beta = 0.334$), and digital participation ($\beta = 0.187$) are the strongest predictors of environmental cooperation; (ii) opinion–behavior coevolution generates higher equilibrium cooperation rates than models treating opinion as exogenous, by 12–18 percentage points; (iii) the Chinese social network context is near the critical confidence-bound threshold that separates fragmented from convergent opinion dynamics; and (iv) high digital participation in scale-free networks raises equilibrium cooperation by approximately 14.8 percentage points relative to the baseline scenario.

Several limitations of the present study should be acknowledged. First, the CGSS cross-sectional design precludes causal inference about the direction of opinion–behavior feedback, and the 2SLS approach used in M3 relies on exclusion restrictions whose validity cannot be fully verified. Future longitudinal studies tracking the same individuals' opinions and behaviors over time would enable stronger causal inference about the coevolution dynamics identified here. Second, the simulation model abstracts from several potentially important features of real-world opinion dynamics, including strategic information sharing, media influence, and institutional norm enforcement, which are represented only indirectly through parameter calibration. Third, the focus on China may limit the generalizability of the specific parameter estimates, though the qualitative mechanisms of network density, opinion homophily, and digital participation effects are expected to operate in other contexts with appropriate rescaling.

Future research should pursue three directions. First, panel data analyses tracking the same individuals and their networks over time would enable direct estimation of the lagged effects of opinion change on behavioral adaptation and vice versa, providing empirical estimates of the coevolution coupling parameter $\gamma$ that currently relies on cross-sectional inference. Second, natural experiment designs exploiting exogenous shocks to digital platform access (such as city-level broadband infrastructure roll-outs or platform policy changes) would enable causal identification of the digital participation effect on environmental cooperation. Third, extending the simulation framework to incorporate institutional actors—governments, corporations, and non-governmental organizations—as non-generic agents with distinct update rules and influence mechanisms would enable richer analysis of multi-level governance dynamics in socio-ecological coevolution.

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